Perspectives on hyperspectral optics and remote sensing

Ali Chase, Applied Physics Laboratory – University of Washington, USA
IOCCG Summer Lecture Series, 26 July 2022, Villefranche-sur-Mer, France

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Who am I?

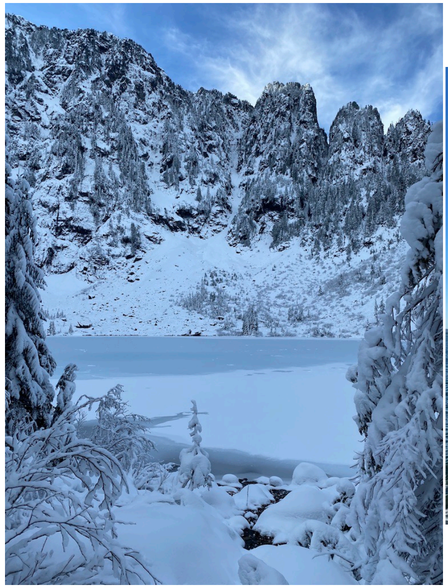
2005 – 2009 B.A. Geology/Environmental Studies, Bowdoin College, Advisor: Collin Roesler

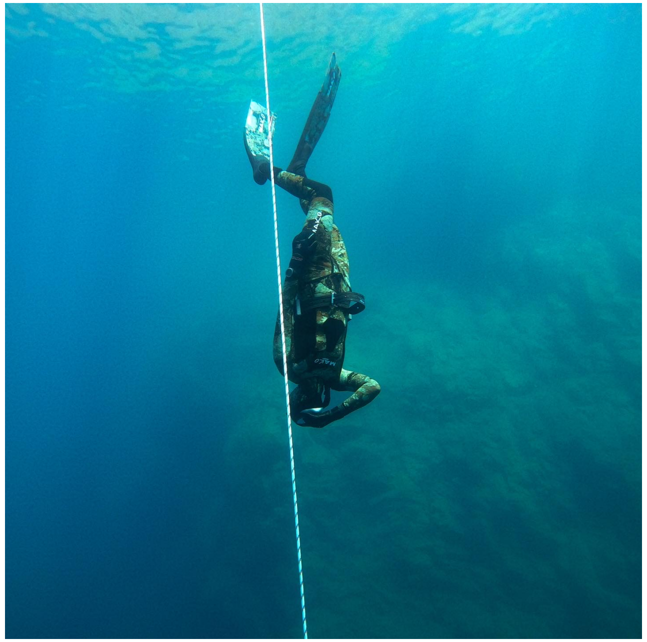
2010 – 2012 Research Associate, Atmospheric & Environmental Research, Lexington MA, USA

2012 – 2020 M.S. & PhD Oceanography, University of Maine, Advisors: Emmanuel Boss & Lee Karp-Boss

2020 – present Postdoc, AIRS Department, Applied Physics Laboratory, University of Washington

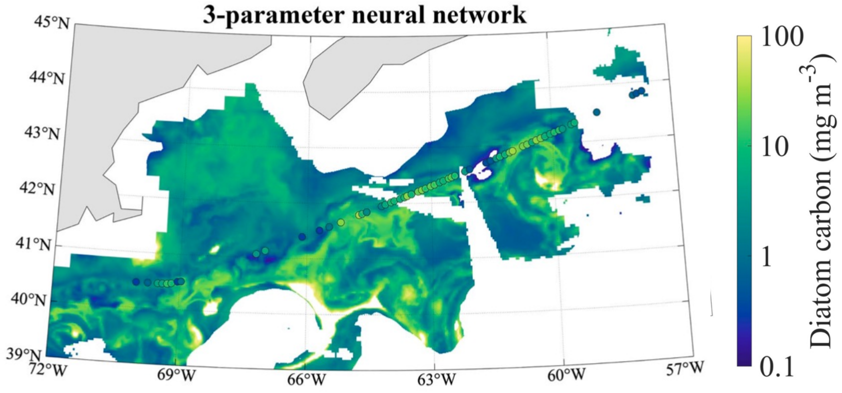
Ocean Optics Summer Course, 2011
Darling Marine Center, Maine USA





Current areas of research

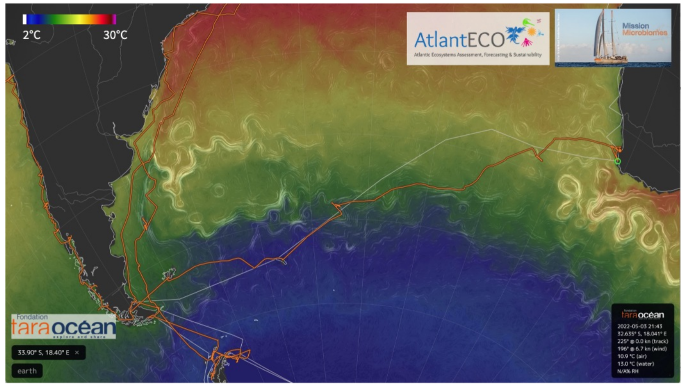
1. Algorithms for remote sensing observation of phytoplankton community composition



2. Open-source tools for plankton image classification using deep learning networks

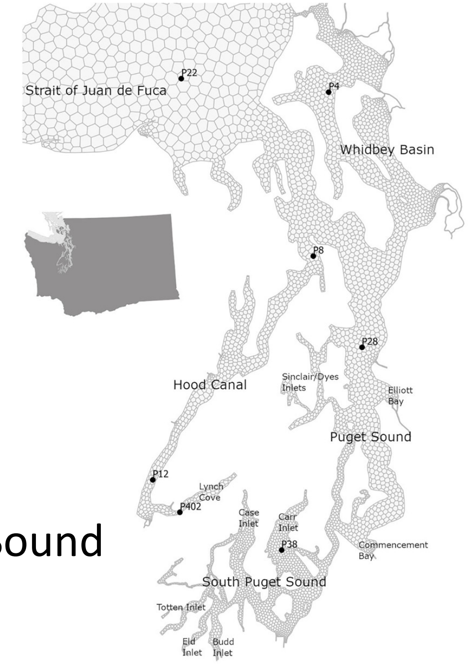
ifcbUTOPIA

User-friendly Tools for Oceanic Plankton Image Analysis (UTOPIA) is for use with data from the Imaging FlowCytobot (IFCB)



3. Observing & exploring phytoplankton at the (sub)mesoscale using continuous optics & imaging systems

4. Phytoplankton communities and environmental parameters in the Puget Sound

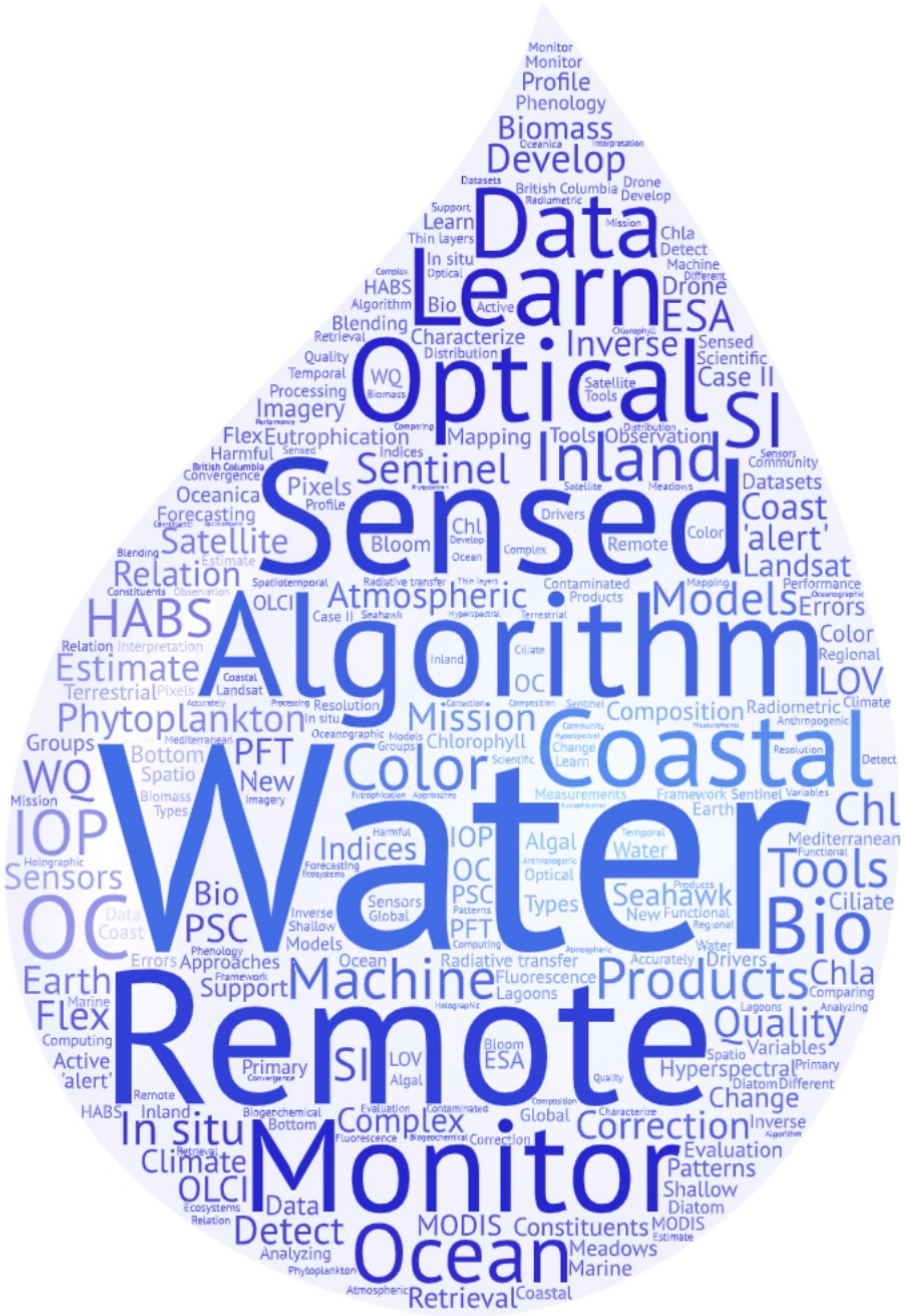


What do you like to do outside of science?

Mentimeter

- Bike trips
- Hang out with dogs
- Writing proposals
- camping, walking, outdoor sports
- Canoe
- Surfing! Reading science fiction! Coffee on Sunday mornings.
- Scuba diving
- Climbing
- Boating

21



Monitor
Profile
Phenology
Biomass
Develop
British Columbia
Drone
Data
Chla
Learn
In situ
Detect
HABS
Drone
ESA
Optical
Inverse
Characterize
Blending
SI
Case II
WQ
Processing
Imagery
Satellite
Tools
Flex
Eutrophication
Mapping
Observation
Harmful
Inland
Sentinel
Oceanica
Pixels
Sensed
Datasets
Coast
Forecasting
'alert'
Satellite
Bloom
Remote
Landsat
Relation
Atmospheric
Models
Errors
HABS
Algorithm
Color
Estimate
LOV
Terrestrial
Phytoplankton
Mission
Composition
Radiometric
Coastal
Groups
Chlorophyll
Color
WQ
PFT
New
Bottom
Spatio
Chl
IOP
Water
Indices
Tools
Sensors
Seahawk
Ciliate
OC
Bio
PSC
Bio
Mediterranean
Earth
Machine
Products
Chla
Flex
Remote
Quality
Approaches
Support
Radiative transfer
Fluorescence
Lagoons
SI
Primary
LOV
ESA
Hyperspectral
Variables
Active
'alert'
Change
Complex
Correction
In situ
Monitor
Evaluation
Climate
Patterns
OLCI
Shallow
Data
Diatom
Detect
MODIS
Constituents
Ocean
Meadows
Marine
Analyzing
Retrieval
Coastal

Lecture Motivation

The potential to extract information from hyperspectral optical & ocean color measurements (in situ and remote sensing) receives a great deal of attention. Technology advances mean that hyperspectral data will become more and more ubiquitous. Understanding what has been done, current limitations, and the opportunities will help us move forward as effectively as possible.

Slide content inspired by and with info from Heidi Dierssen (UConn), Patrick Gray (Duke), & many papers (see references at the end)

Lecture outline & key topics

Current capabilities of hyperspectral optics & remote sensing

Approaches to extracting information from hyperspectral measurements

Applications to the coastal & complex aquatic ecosystem community

Lecture outline & key topics

Current capabilities of hyperspectral optics & remote sensing

Approaches to extracting information from hyperspectral measurements

Applications to the coastal & complex aquatic ecosystem community

History of hyperspectral optics

1970s – Foundational work for much of today's ocean color remote sensing research

Assessment of Aquatic Environments by Remote Sensing (Adams et al., 1977)

- Laboratory reflectance measurements; "fingerprints" of different algal types

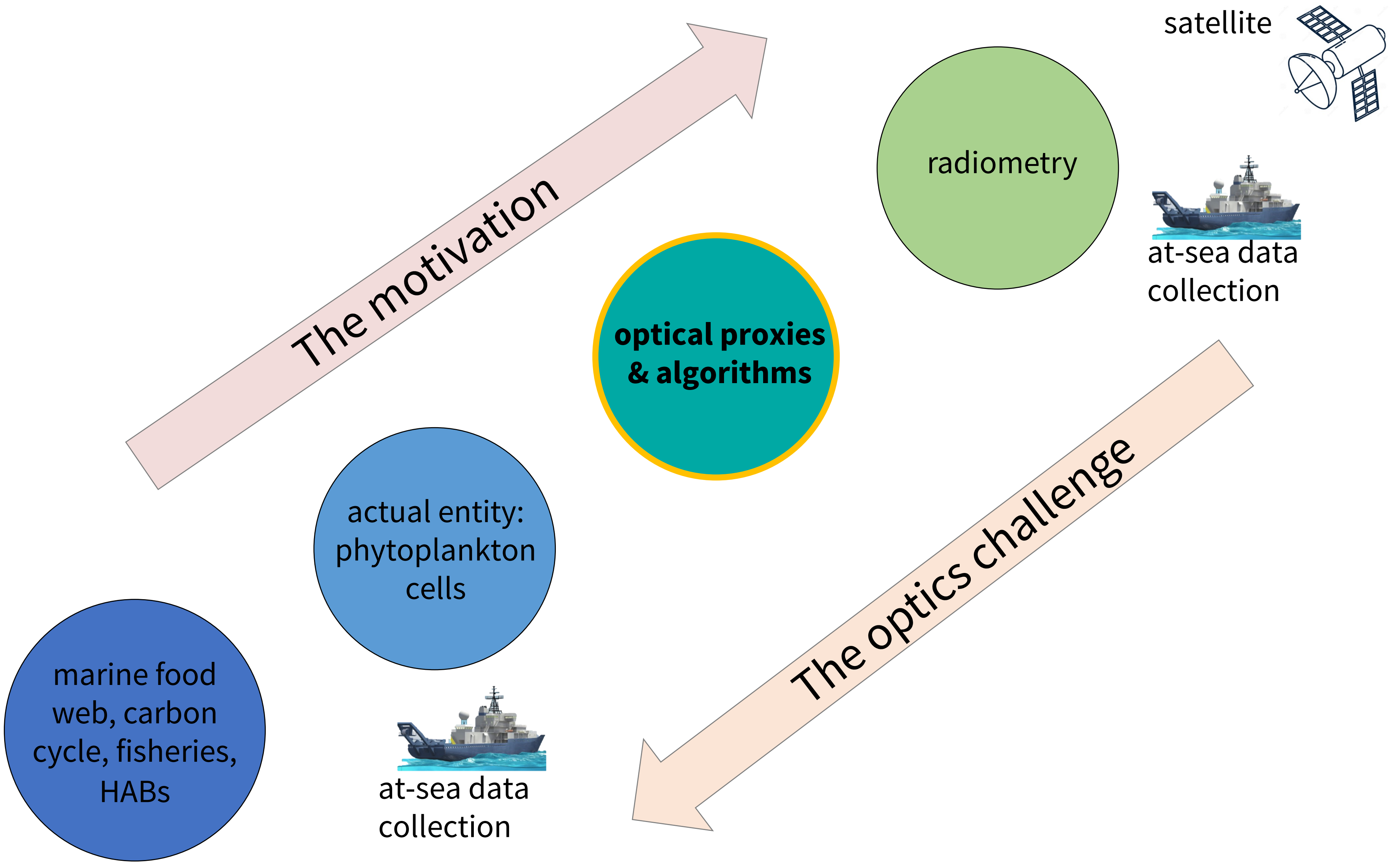
From Morel and Prieur, 1977:

"If we attempt to distinguish between more than two absorbing agents, such as different chlorophyll forms, pheopigments, or yellow substance, etc., the above conclusion remains valid according to the available results for their specific absorption spectra. The fact that, whatever the wavelength, several absorbers come into play does not prevent solution of the problem, at least from a theoretical point of view. Multispectral measurements in relative units at N+ 1 wavelengths allow the inference of concentration of N absorbing compounds…Further efforts are required to develop such a catalogue of spectral signatures."

Hydrolight software (Mobley, 1994)

- Radiative transfer-based simulations of spectral reflectance, used in many types of studies

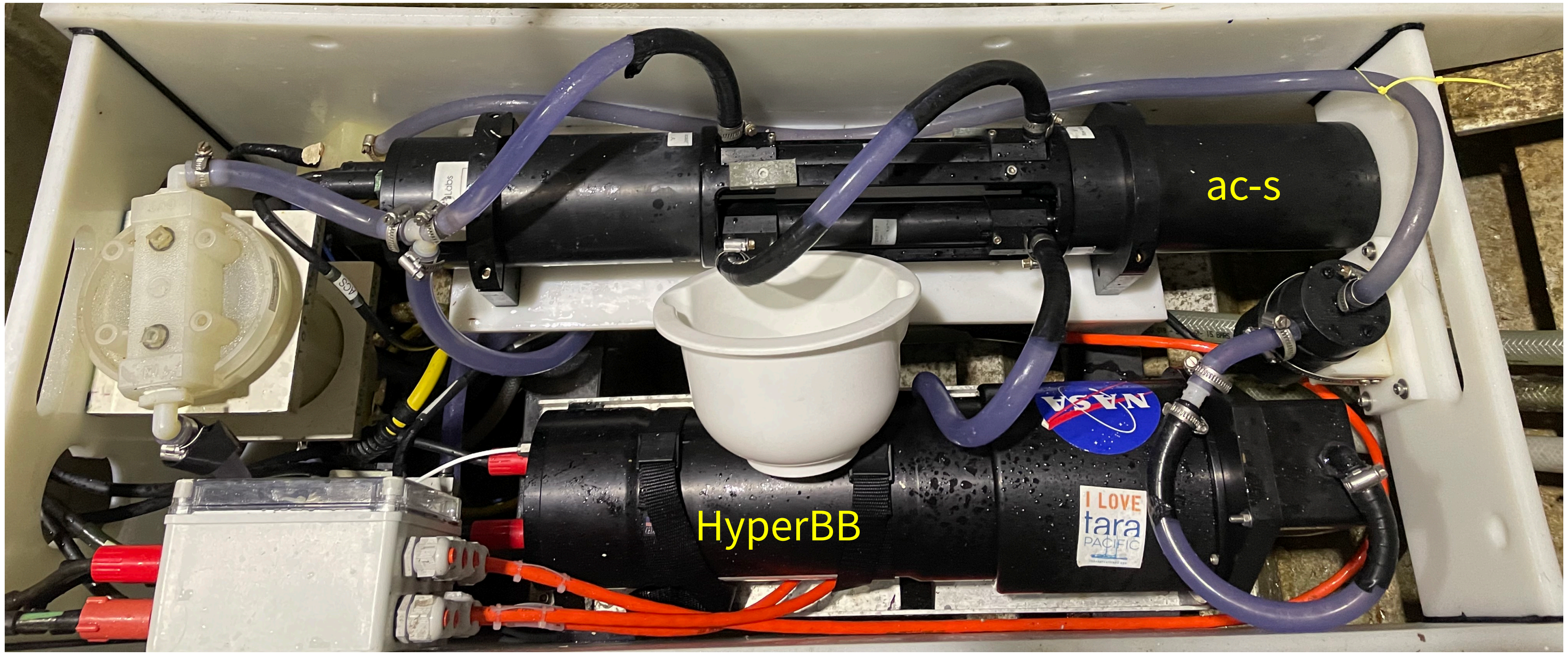
Ocean color remote sensing: the motivation & the challenge



Adapted from M. J. Perry

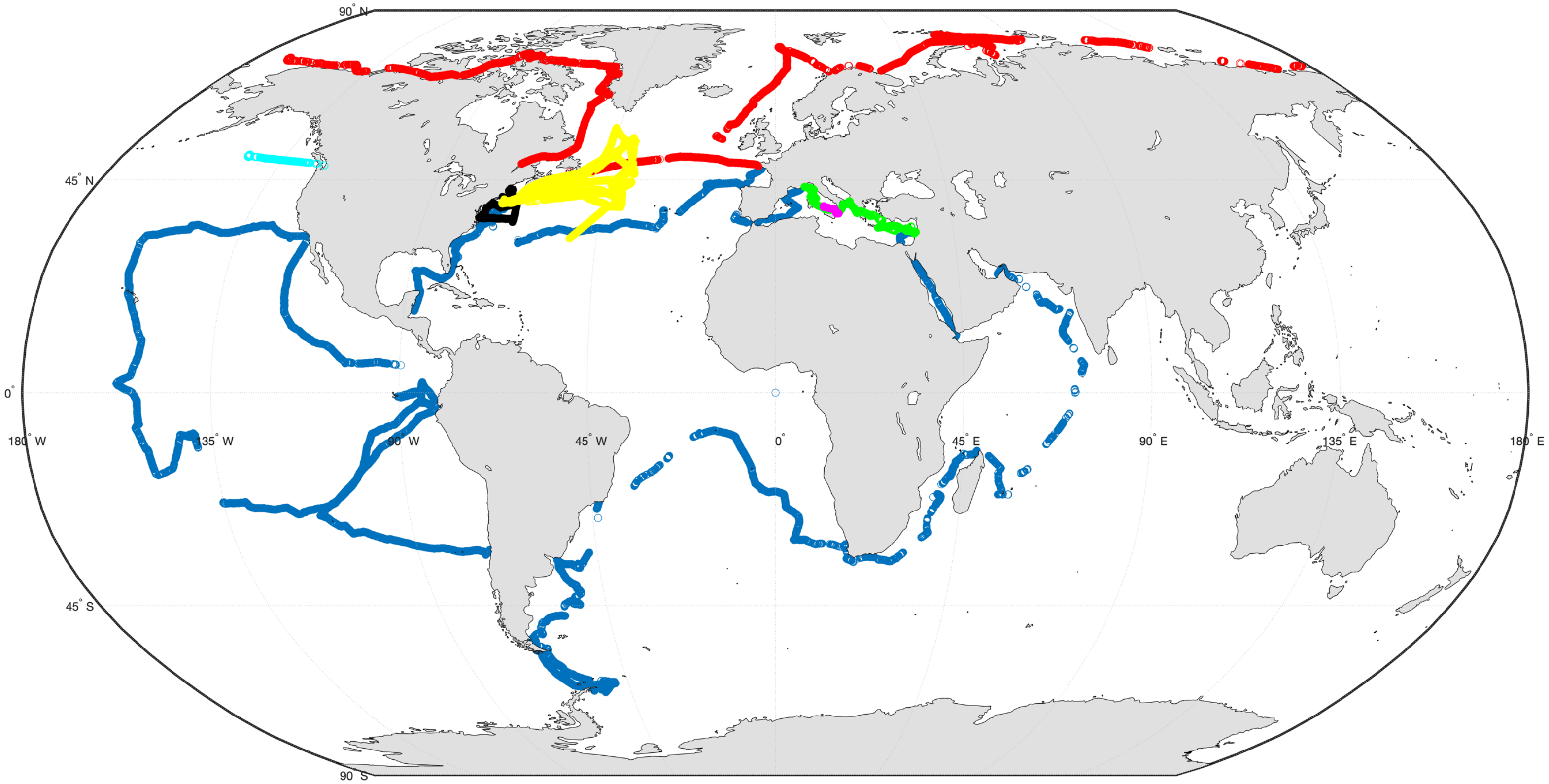
In situ instrumentation & laboratory measurements

- ac-s (absorption and attenuation in the visible wavelengths)
- Bench-top spectrophotometers
- HyperBB (backscattering)
- ALFA spectral fluorescence
- Radiometric measurements (e.g., hyperPro, hyperSAS, TriOS, Triaxus)



Spectral absorption & attenuation from underway ac-s deployments

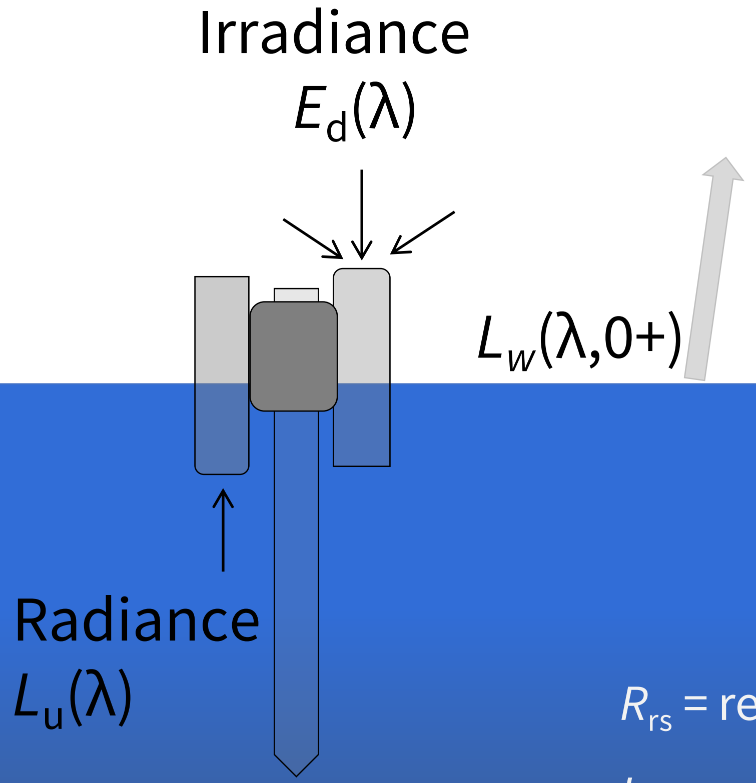
- Tara Oceans
- Tara Polar Circle
- NAAMES
- SABOR
- Line P
- Tara Mediterranean
- PEACETIME

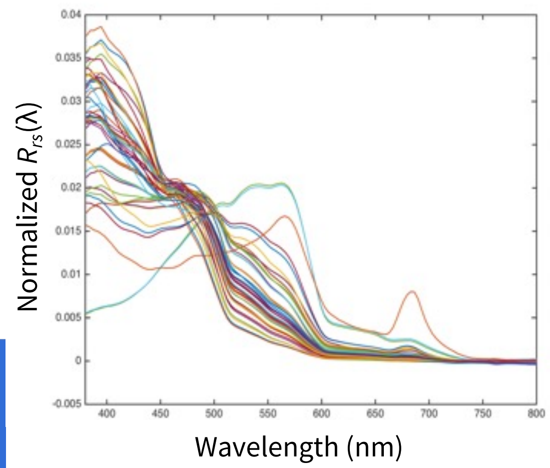


ac-s

Hyperspectral $R_{rs}(\lambda)$ measured in situ

$$R_{rs}(\lambda) = \frac{L_w(\lambda,0+)}{E_d(\lambda)}$$





R_{rs} = remote-sensing reflectance

L_w = water-leaving radiance

L_u = upwelling radiance

E_d = downwelling irradiance

Hyperspectral fluorescence emission & spectral deconvolution

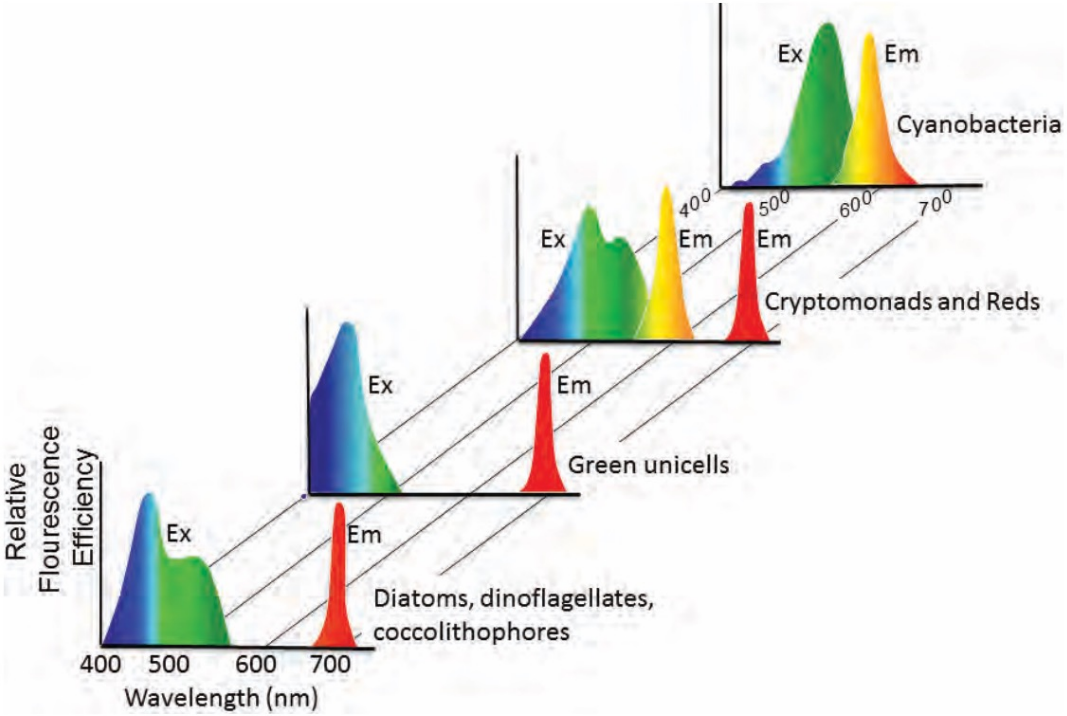
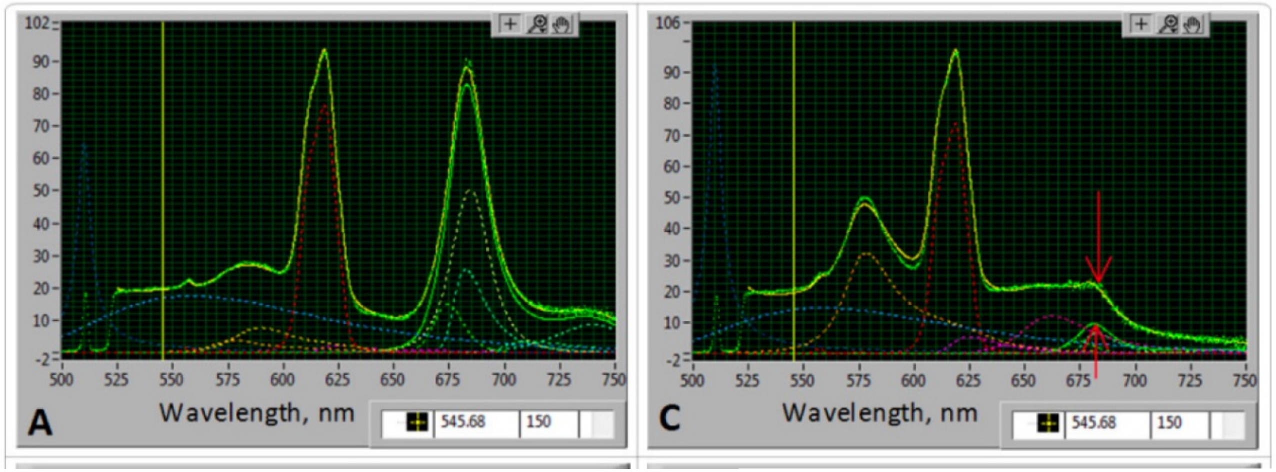
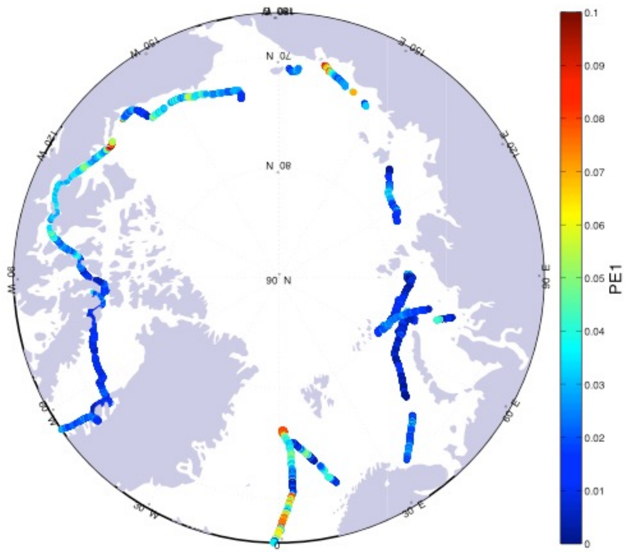


Figure 2.4 General characteristics of fluorescence excitation (Ex) and emission (Em) spectra for various groups of phytoplankton. Phytoplankton taxa with phycobiliproteins (cyanobacteria, cryptomonads) have distinctive emission peaks compared to other groups. Excitation spectra exhibit more subtle variations according to photosynthetic accessory pigment composition. Modified from Yentsch and Phinney (1985).



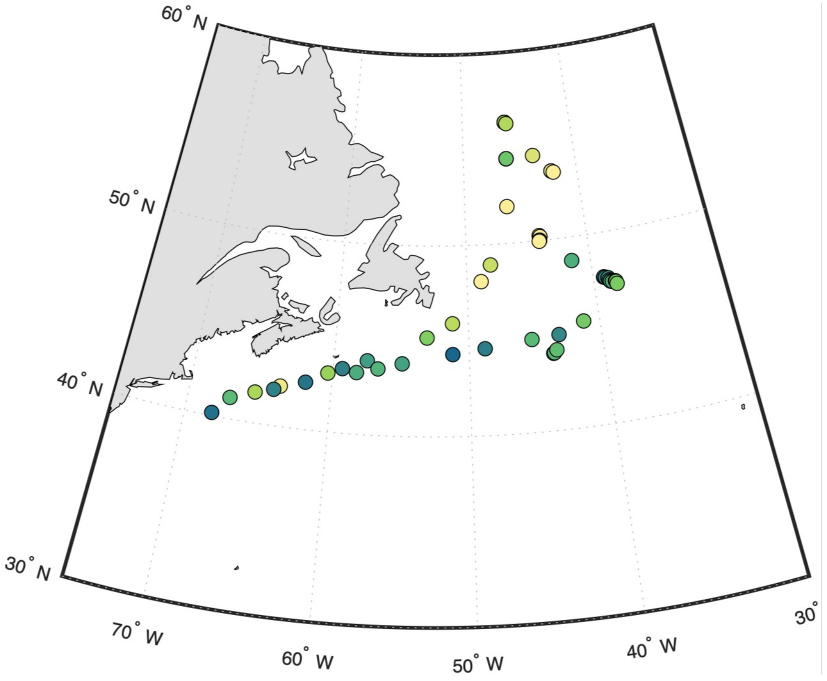
Chekalyuk and Hafez, 2013



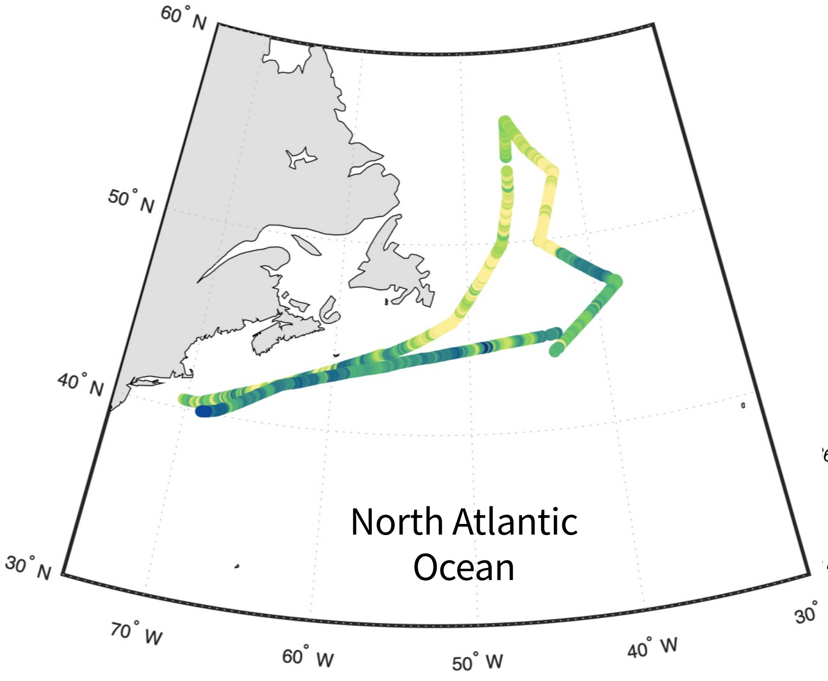
Tara Polar Circle, 2013

Trade-offs for spatial and temporal resolution – how can we scale up to regional and global views?

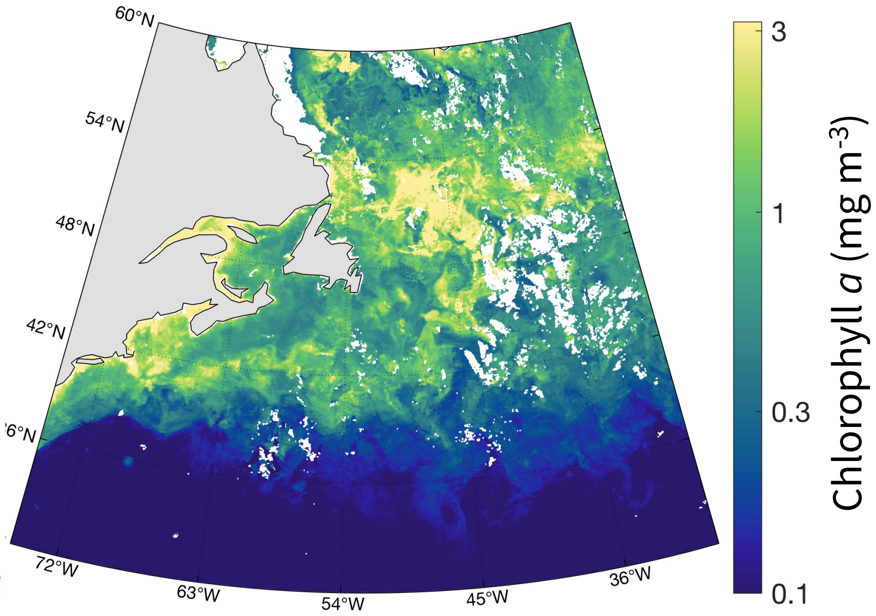
Discrete samples



Ship-board continuous measurements

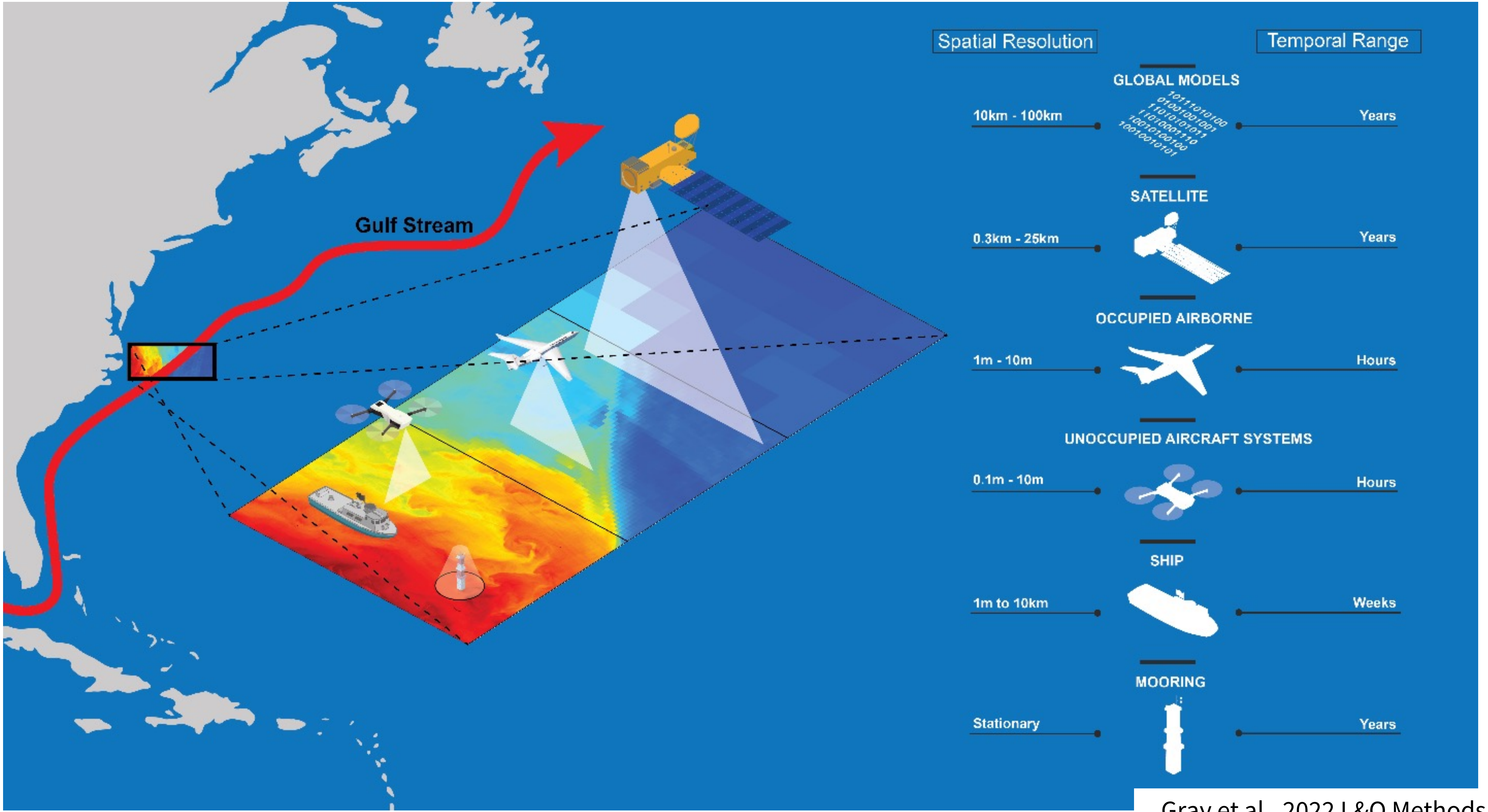


Satellite remote sensing



Direct measurement of cells & processes

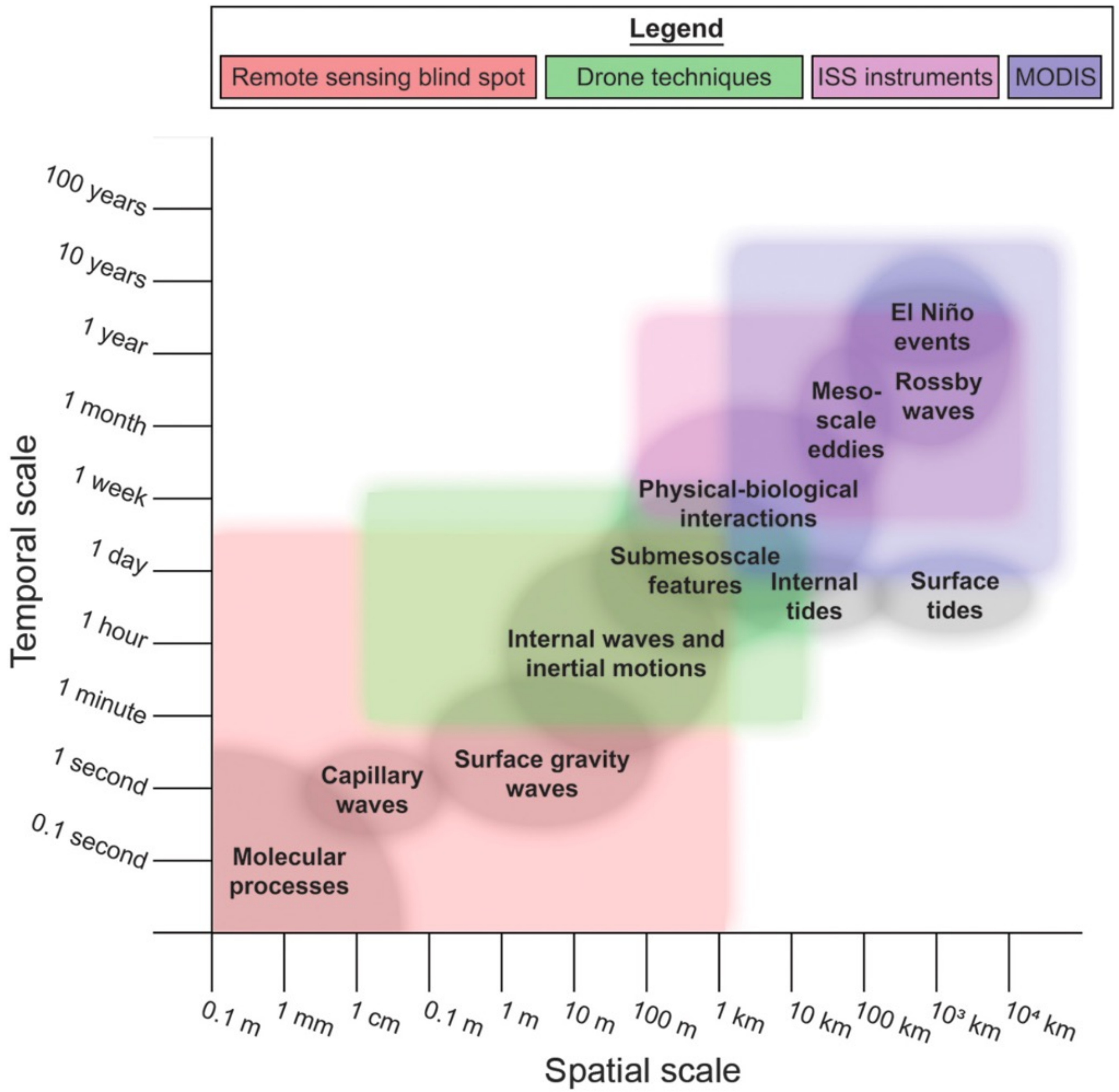
Spatial & temporal resolution



Gray et al., 2022 L&O Methods

Drones address an observational blind spot for biological oceanography

Patrick Clifton Gray*, Gregory D Larsen, and David W Johnston



Gray et al., 2022 Front Ecol Environ

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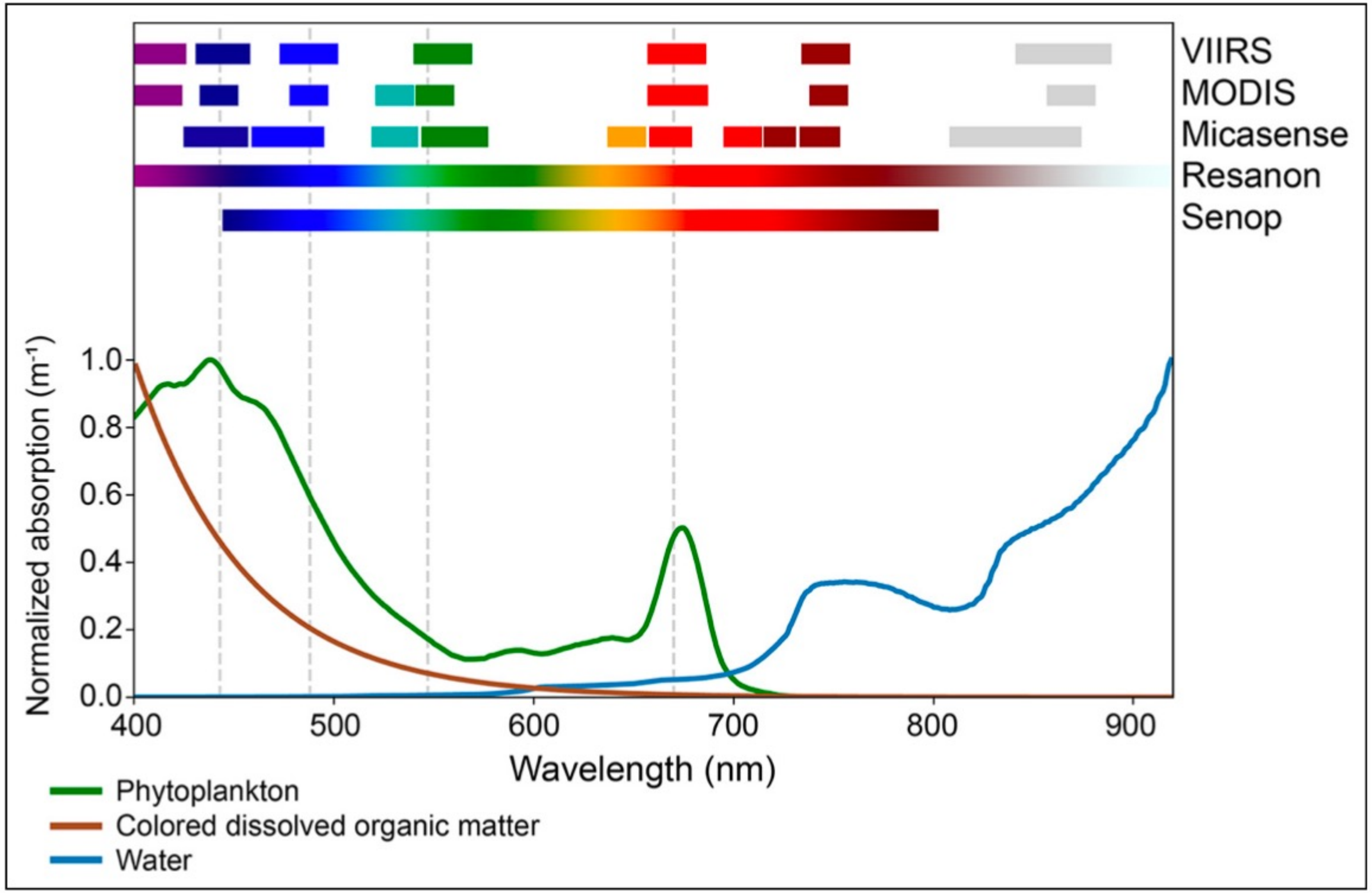


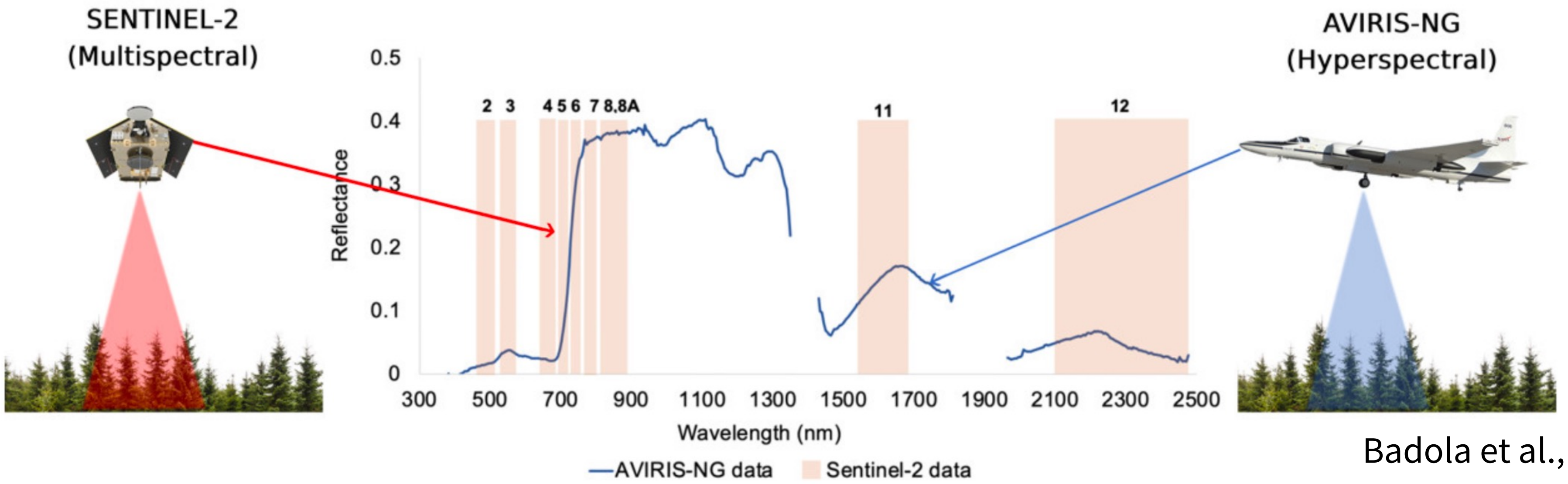
Gray et al., 2022 Front Ecol Environ

Ocean Color measurements made from UAVs (a.k.a. drones)

- Well suited for coastal and estuarine areas (perhaps less so for open ocean work)
- Point spectrometer measurements are simpler and may provide better data in some cases compared to imagery
- Multispectral cameras are currently much cheaper and can be sufficient in many cases
- Challenges arise from viewing angle geometries and subsequent variability of sea and sky radiance across an image
- In situ measurements can be used to accurately remove reflected skylight during calculations of R_{rs} (Gray et al., 2022 L&O Methods)
- Longer flight times from large, gas-powered drones would improve the limited coverage of a typical drone flight
- RGB imagery can be used to visualize complex regions

Airborne Imaging Spectrometry

High-resolution airborne hyperspectral sensors: AVIRIS, AISA, HyMAP, PRISM, APEX, OMIS, PHI, PHILLS

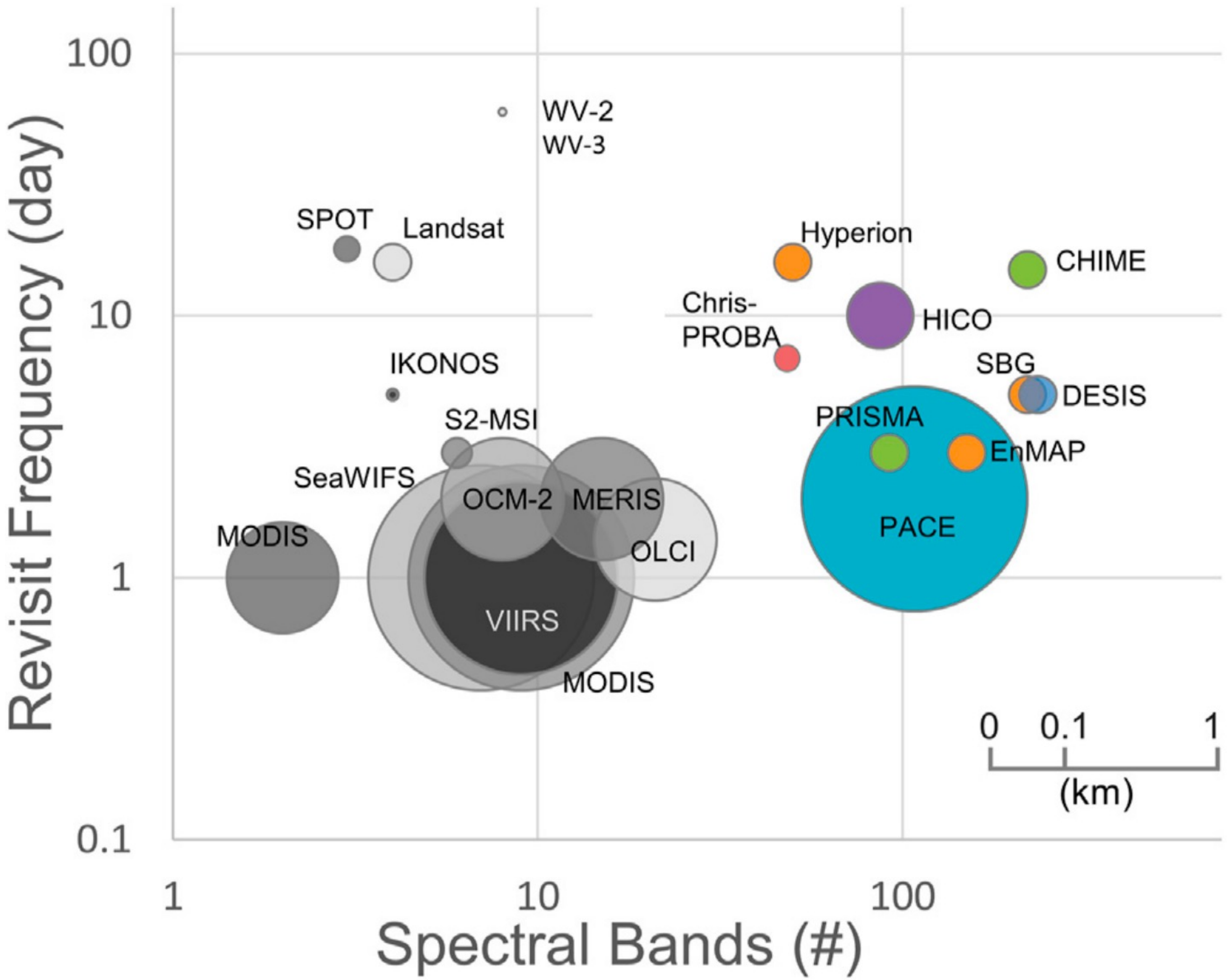


Badola et al., 2021

- Good for water quality algorithm development and applications in inland and coastal waters
- “Medium-scale” surveys of macrophytes (e.g., kelp, seagrasses), coral reefs, water contaminants
- Useful for design tests for satellite-based systems, and/or test atmospheric correction procedures
- Limited in spatial coverage and revisit time
- Some challenges with relatively low signal-to-noise ratio (SNR) and a limited dynamic range

Giardino et al., 2019

Spectral, spatial, and temporal resolution of ocean color missions



Also:
SCHIMACHY
GOCI
GLIMR
AHSI

Dierssen et al., 2021
Modified from Hestir et al., 2015

HICO – Hyperspectral Imager for the Coastal Ocean

- 2009-2014 on the ISS
- 3.6 nm spectral resolution across 400-900 nm in the visible
- ~90 m spatial resolution
- User-selected target (~2000 images per year)

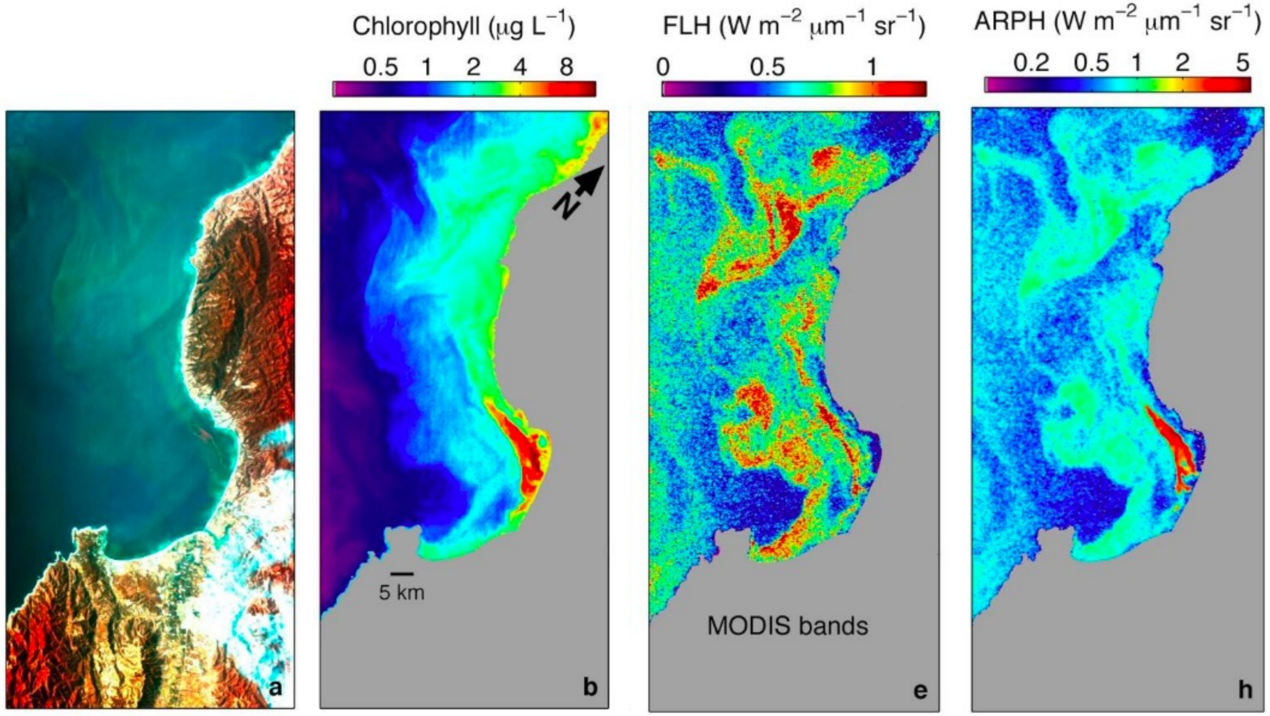


Image of Monterey Bay, CA, USA in fall 2011

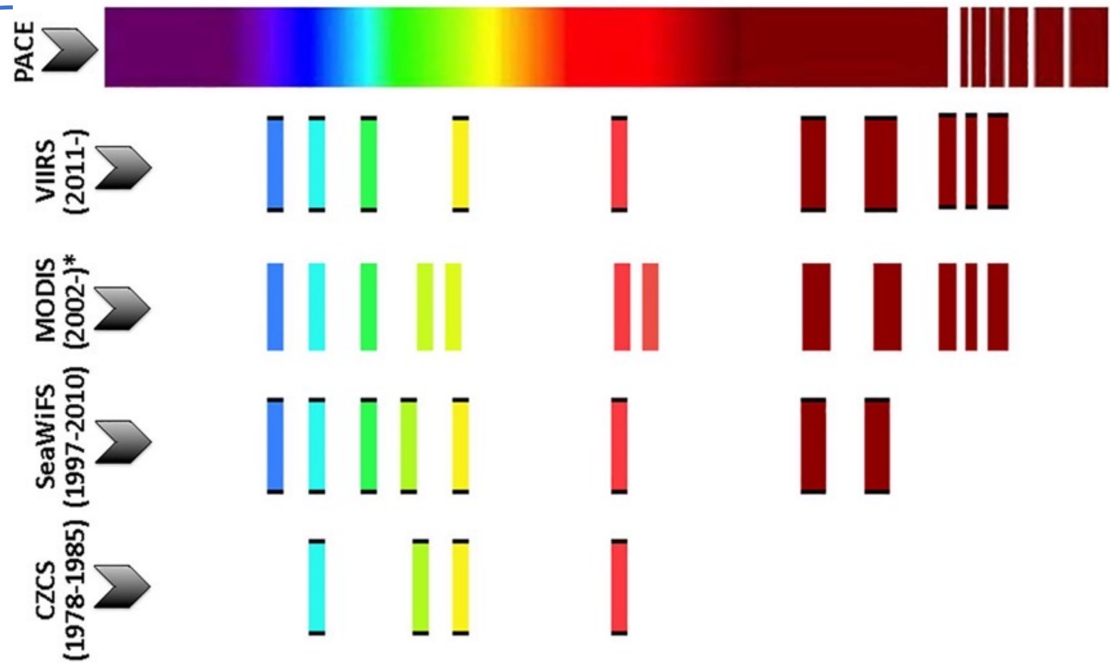
ARPH = adaptive reflectance peak height

Ryan et al., 2014

PACE - Plankton, Aerosol, Cloud, ocean Ecosystem

- Hyperspectral OCI (Ocean Color Instrument) and two polarimeters
- 5 nm resolution from 320 – 890 nm, also 7 SWIR bands
- 1 km spatial resolution
- Anticipated launch in January 2024

NASA Satellite ocean color missions



PACE simulation https://pace.gsfc.nasa.gov/

GLIMR – Geostationary Littoral Imaging and Monitoring Radiometer

- Planned launch in 2026, geostationary over the Gulf of Mexico w/views of North & South America
- Hyperspectral imager for 340-1040 nm
- 300 m spatial resolution at nadir, ~hourly measurements
- Two main science goals:
  1. Understand the processes contributing to rapid changes in phytoplankton growth rate and community composition.
  2. Quantify how high frequency fluxes of sediments, organic matter, and other materials between and within coastal ecosystems regulate the productivity and health of coastal ecosystems.

https://eos.unh.edu/glimr

CHIME - Copernicus Hyperspectral Imaging Mission for the Environment

- Planned launch around 2029
- Lake and coastal ecosystem monitoring
- AVIRIS images and coincident ground measurements to aid with instrument development
- Additional coordination with PRISMA and DESIS

https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Going_hyperspectral_for_CHIME

Lecture outline & key topics

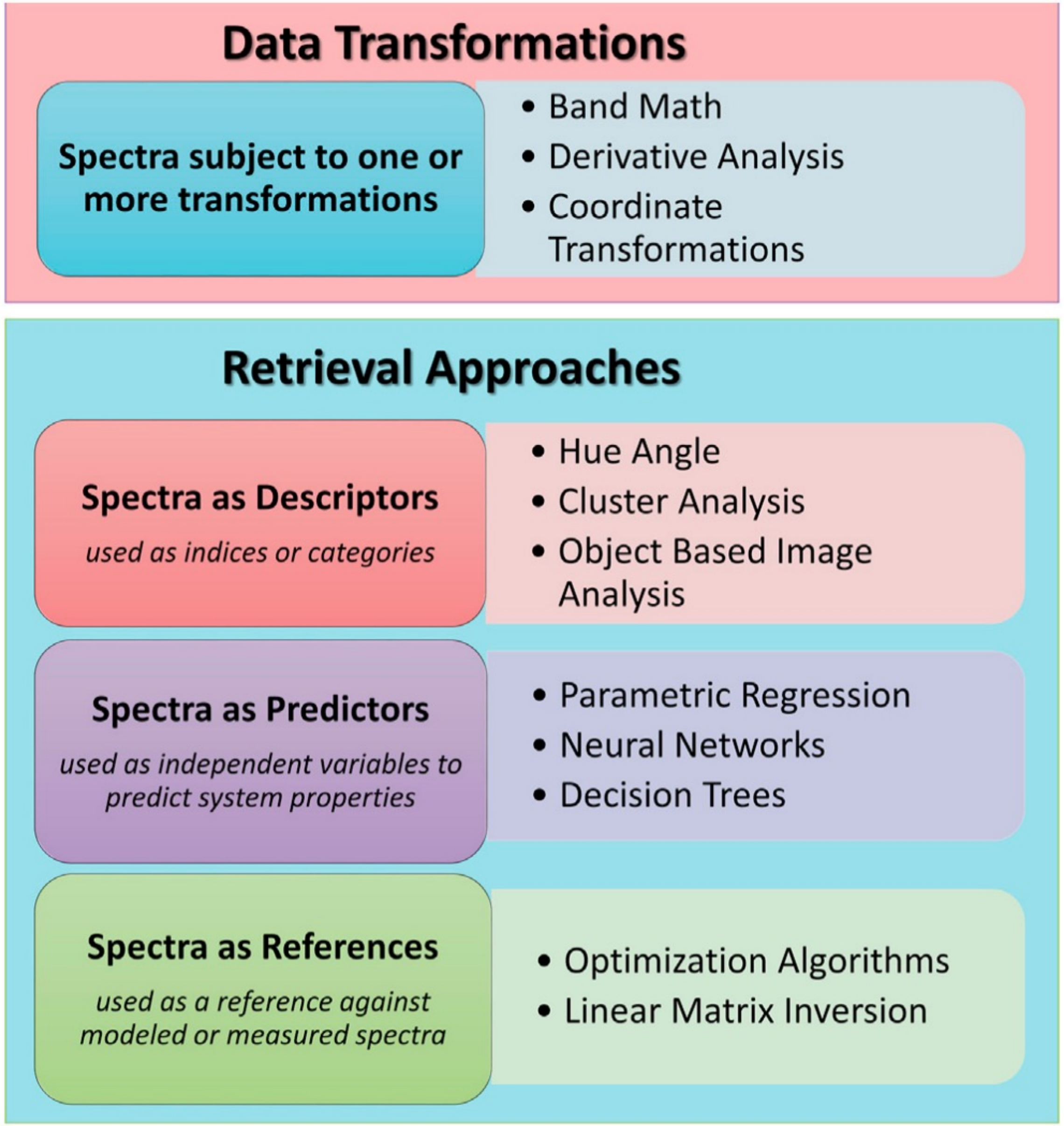
Current capabilities of hyperspectral optics & remote sensing

Approaches to extracting information from hyperspectral measurements

Applications to the coastal & complex aquatic ecosystem community

Living up to the Hype of Hyperspectral Aquatic Remote Sensing: Science, Resources and Outlook

Heidi M. Dierssen[1], Steven G. Ackleson[2], Karen E. Joyce[3], Erin L. Hestir[4], Alexandre Castagna[5], Samantha Lavender[6] and Margaret A. McManus[7]*



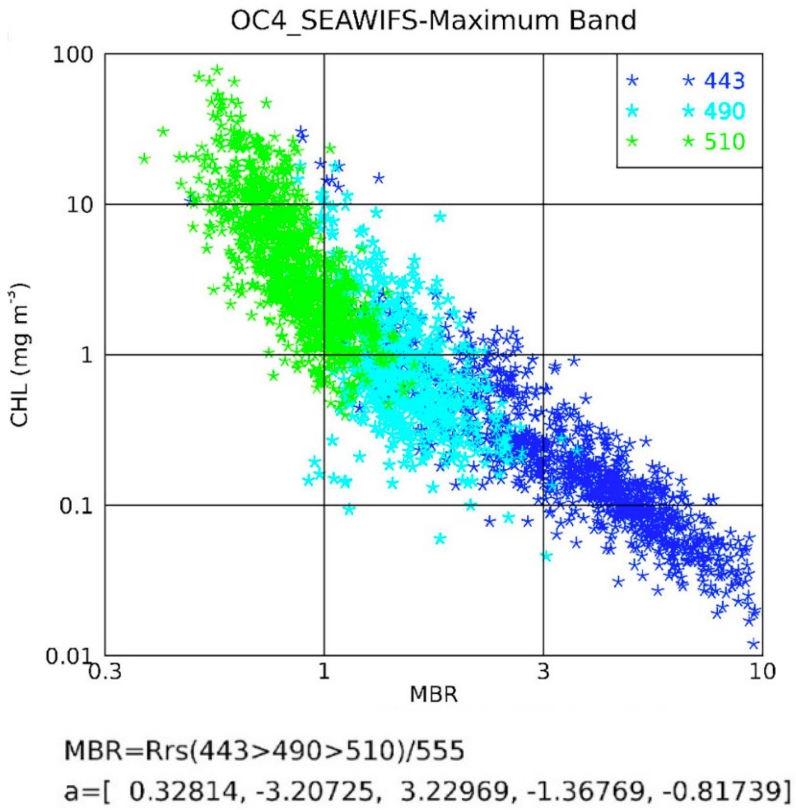
Dierssen et al., 2021

Approaches to extract information from hyperspectral data

Approach	Input measurements	Result/product	Target/validation data	Reference
Direct use of optical measurements: Similarity Index, EOF, and/or clustering analysis	$a_\phi(\lambda)$ & 4th derivative of spectra	% contribution of *G. breve*	*G. breve* field and culture data	Millie et al. 1997
	2nd derivative of $a_\phi(\lambda)$	Diatom contribution to Chl *a*	CHEMTAX diatom Chl *a*	Isada et al. 2015
	$a_p(\lambda)$	Cell counts and Chl *a* fraction of *G. breve*	*G. breve* field and culture data	Kirkpatrick et al. 2000
	2nd derivative of $R_{rs}(\lambda)$	Detection of *Phaeocystis* blooms	Microscopic identification of phytoplankton	Lubac et al. 2008
	4th derivative of $a_\phi(\lambda)$ and $R_{rs}(\lambda)$	Differentiation of phytoplankton groups; cyanobacteria dominance in inland waters	Cultures, Hydrolight simulations, field $R_{rs}(\lambda)$ measurements	Xi et al. 2015; 2017
	Derivatives of $a_p(\lambda)$ or $a_\phi(\lambda)$	Pigment assemblages or concentrations	HPLC pigments or Chl *a* concentration from fluorescence	Catlett and Siegel 2018; Shaju et al. 2015; Torrecilla et al. 2011
	$R_{rs}(\lambda)$	Pigment concentrations	HPLC pigments	Bracher et al. 2015; Kramer et al. 2022
	$a_\phi(\lambda)$ and $R_{rs}(\lambda)$, and derivatives	Bio-optical water categories	HPLC pigments	Uitz et al. 2015
	$L_u(\lambda)$	Relative phycoerythrin concentrations	PE concentration	Taylor et al. 2013
	$a_\phi(\lambda)$ and $R_{rs}(\lambda)$, and $a_\phi(\lambda)$ derivatives	*K. brevis* relative bloom strength	*K. brevis* absorption spectrum	Craig et al. 2006
	$R_{rs}(\lambda)$	Apparent Visible Wavelength		Vandermuelen et al. 2020; Dierssen et al. 2022
Methods of spectral inversion: Spectral inversion and Gaussian decomposition	$a_p(\lambda)$ or $a_\phi(\lambda)$	Pigment concentrations or absorption	HPLC pigments	Aguirre-Gomez et al. 2001; Chase et al. 2013; Hoepffner and Sathyendranath 1991, 1993; Liu et al. 2019; Lohrenz et al. 2003; Ye et al. 2019
	$R_{rs}(\lambda)$	Contribution of phytoplankton groups to absorption	Microscopic cell counts	Roesler et al. 2004
	$R_{rs}(\lambda)$	Pigment concentrations	HPLC pigments	Chase et al. 2017; Wang et al. 2016
	$R_{rs}(\lambda)$	$a_\phi(\lambda)$ and Chl *a* concentrations	In situ $R_{rs}(\lambda)$	Pahlevan et al., 2020; Pahlevan et al., 2021

Data Transformations

- Band math, derivative analysis, coordinate transformations (e.g., PCA, PLSR)



O'Reilly and Werdell, 2019

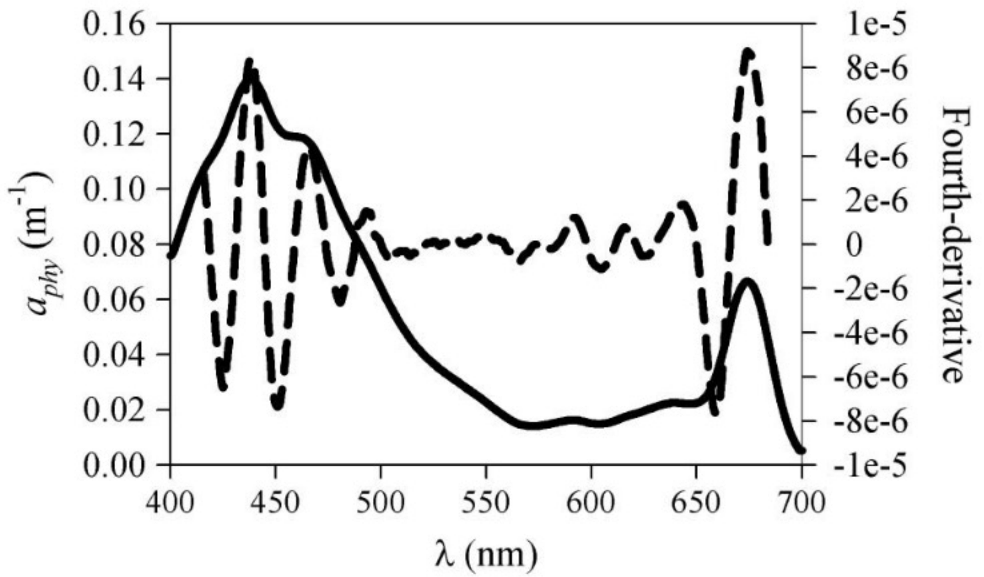


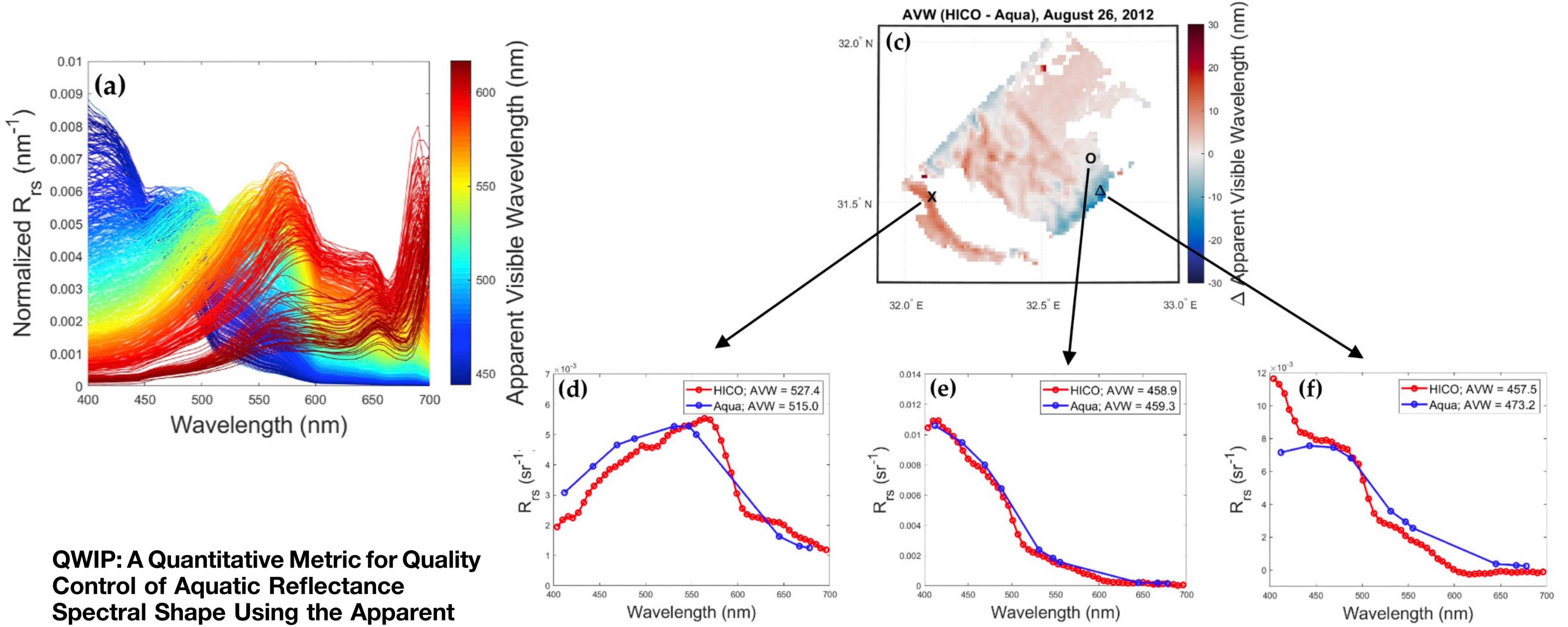
Fig. 2. Example of a smoothed phytoplankton absorption spectrum (solid curve) of the BOUSSOLE time series and its fourth-derivative (dashed curve).

Organelli et al., 2013

Band ratios, wl correlations, lineheight methods

Retrieval Algorithms

- Spectra as descriptors: optical indices, cluster analyses

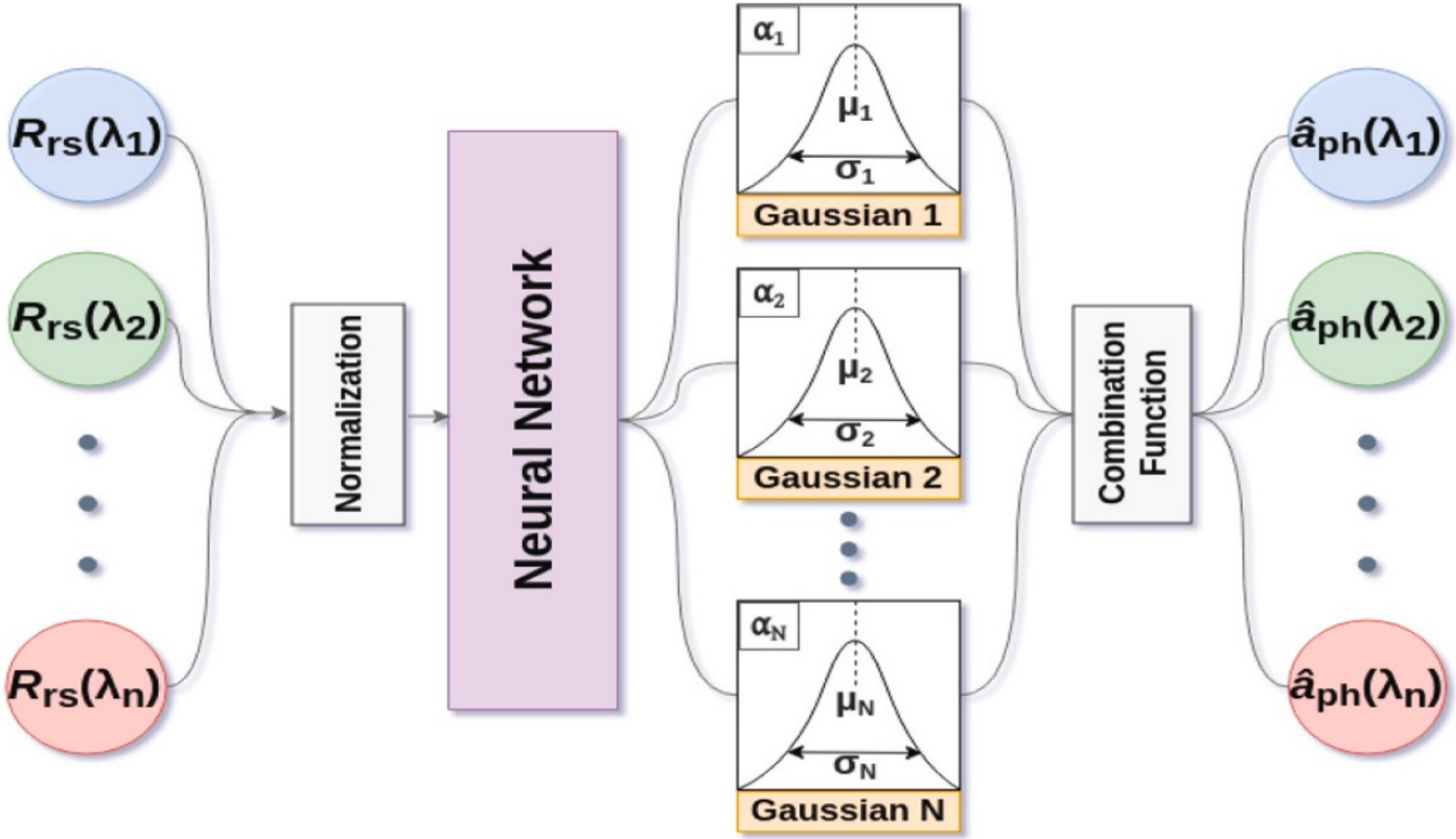


QWIP: A Quantitative Metric for Quality Control of Aquatic Reflectance Spectral Shape Using the Apparent Visible Wavelength

Heidi M. Dierssen[1], Ryan A. Vandermeulen[2,3], Brian B. Barnes[4], Alexandre Castagna[5], Els Knaeps[6] and Quinten Vanhellemont[7]*

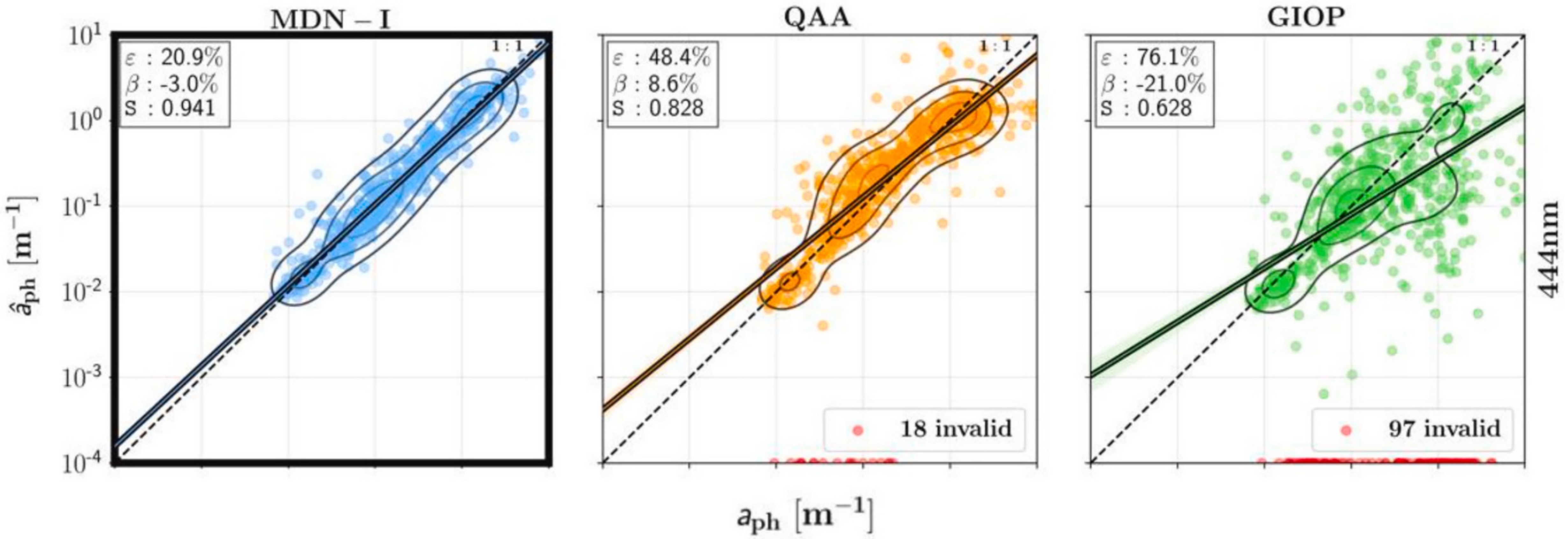
Vandermuelen et al., 2020

Applying Mixture Density Networks (MDN) to hyperspectral R_{rs}



Pahlevan et al., 2021

Applying Mixture Density Networks (MDN) to hyperspectral R_{rs}



Pahlevan et al., 2020

Retrieval Algorithms

- Spectra as references: optimization algorithms, linear matrix inversion

→ Semi-analytical algorithms
→ Definitions of basis vectors using either a library of spectra, or simulated spectra/functions

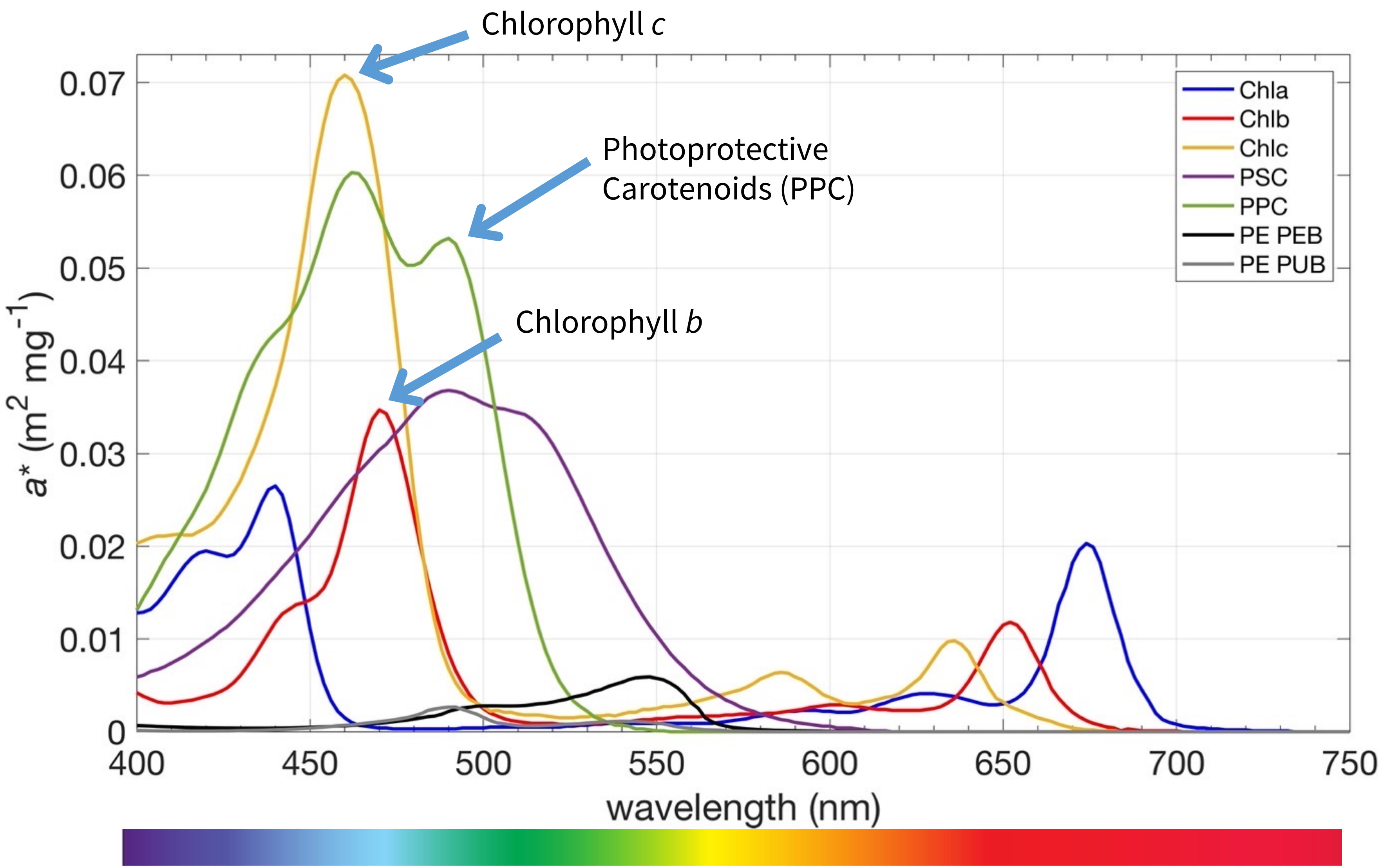
For references categorized by the type of semi-analytic solution, see **Table 4** in:

Review
Progress in Oceanography 160 (2018) 186–212

An overview of approaches and challenges for retrieving marine inherent optical properties from ocean color remote sensing

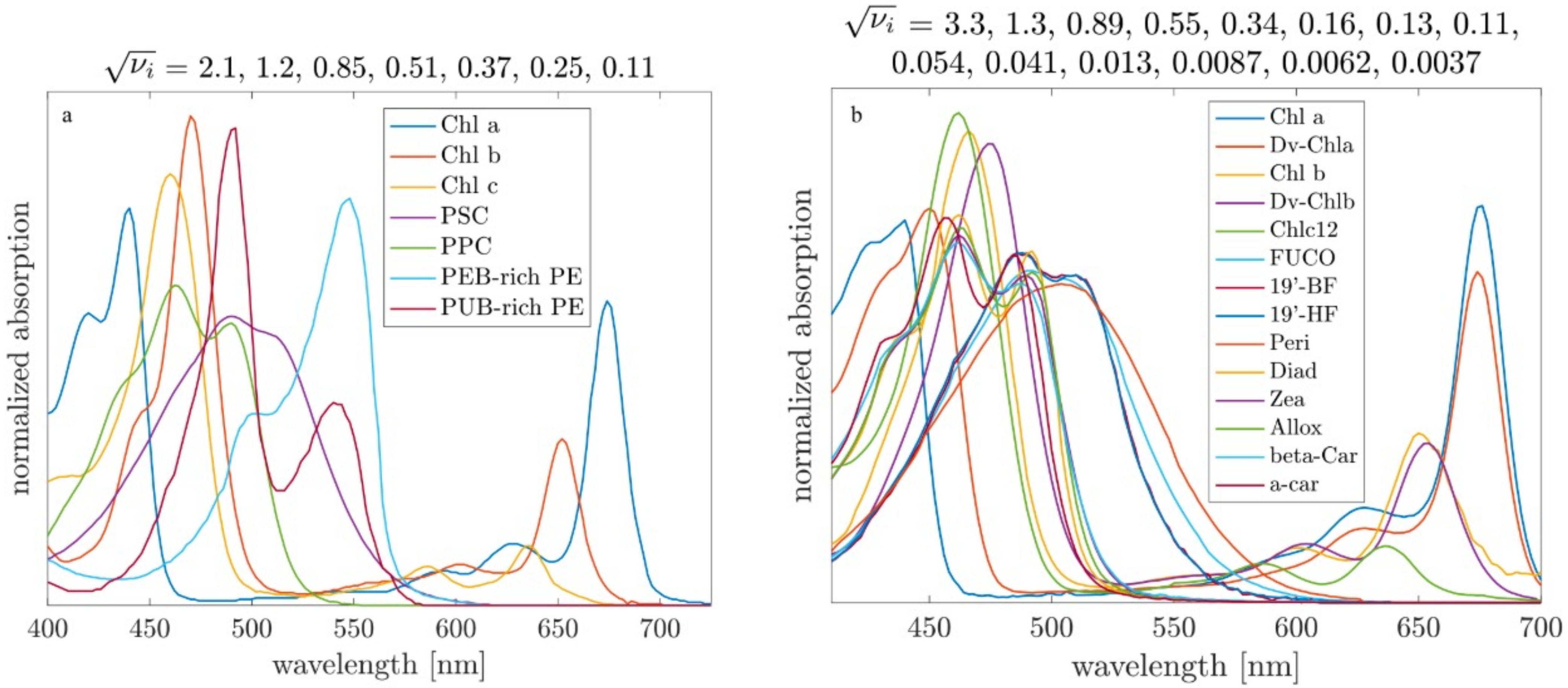
P. Jeremy Werdell[a,*], Lachlan I.W. McKinna[a,b], Emmanuel Boss[c], Steven G. Ackleson[d], Susanne E. Craig[a,e,1], Watson W. Gregg[f], Zhongping Lee[g], Stéphane Maritorena[h], Collin S. Roesler[i], Cécile S. Rousseaux[e,f,2], Dariusz Stramski[j], James M. Sullivan[k], Michael S. Twardowski[k], Maria Tzortziou[l,m], Xiaodong Zhang[n]

Phytoplankton pigments drive spectral absorption features



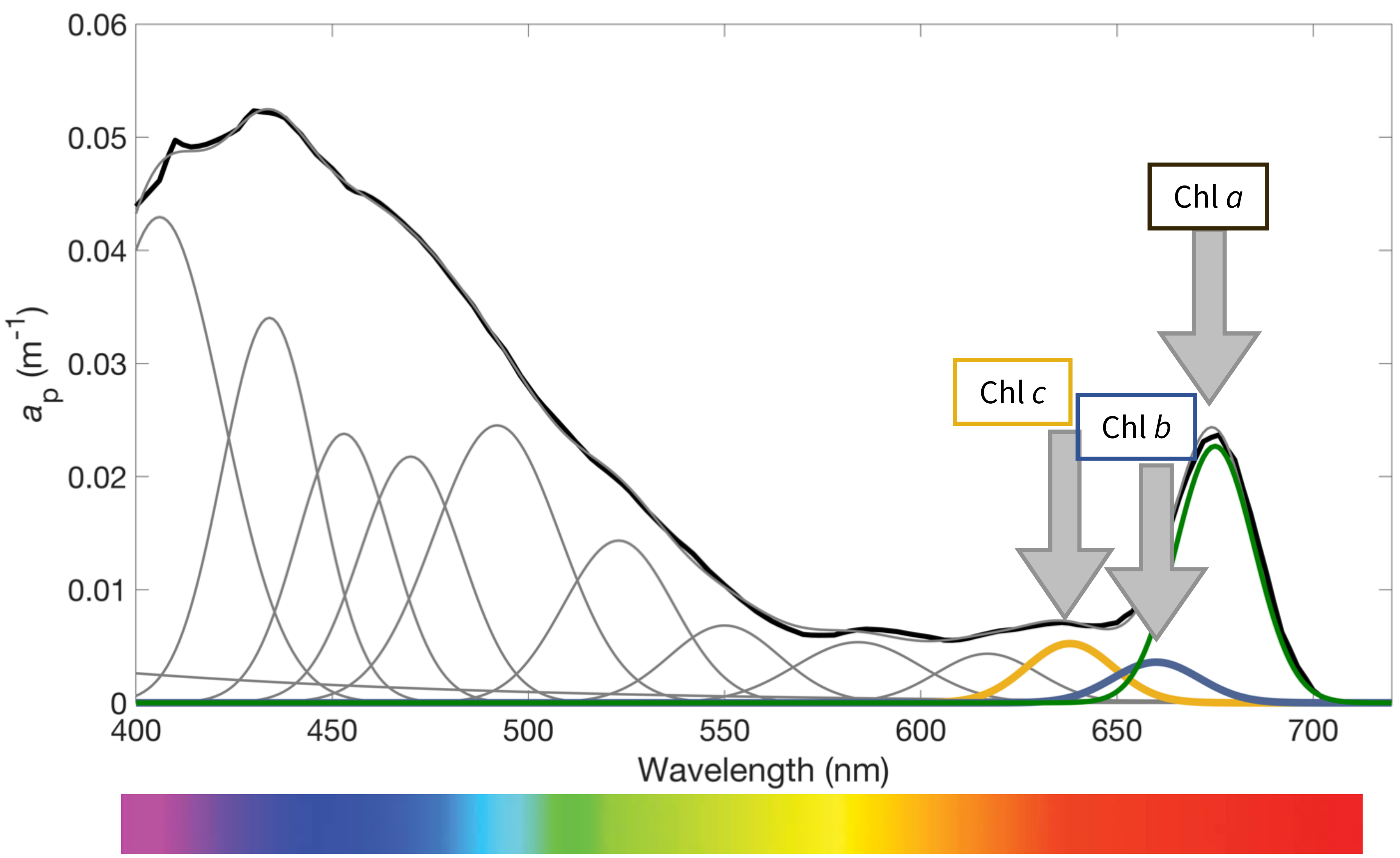
data from Bidigare et al. 1990

But does the inversion problem become ill-posed?



Cael et al. 2020

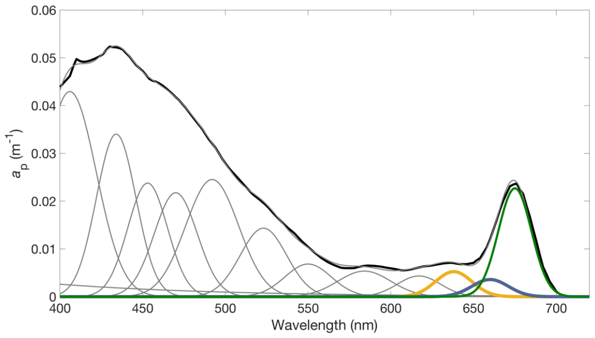
Phytoplankton pigments estimated from ac-s absorption spectra



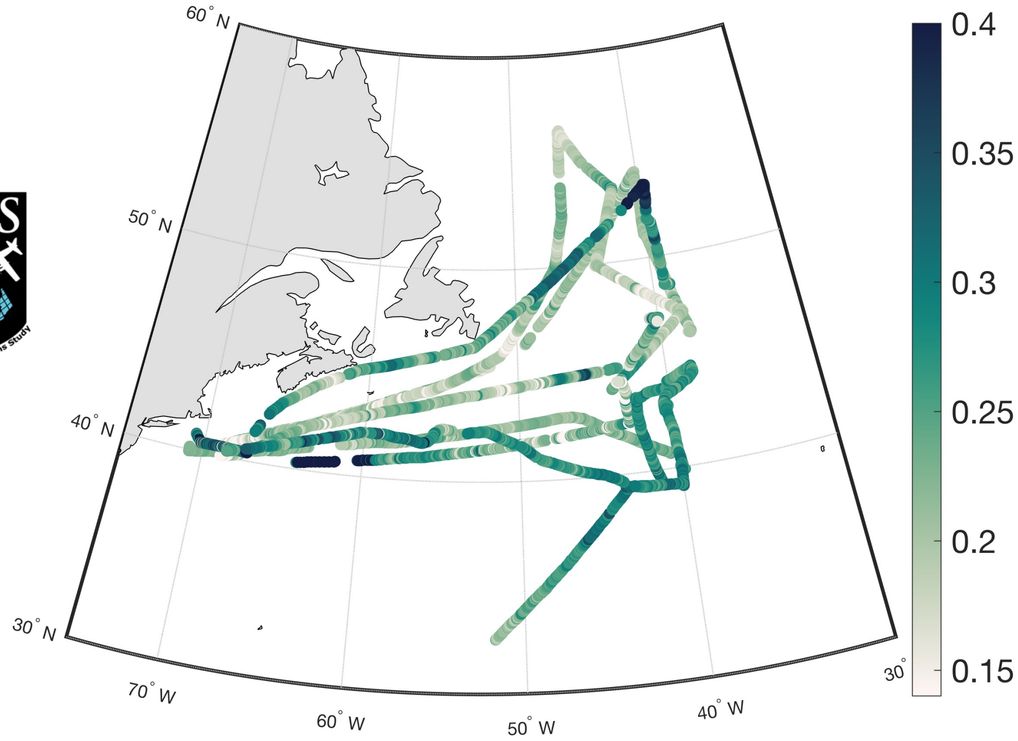
ac-s

Chase et al., 2013

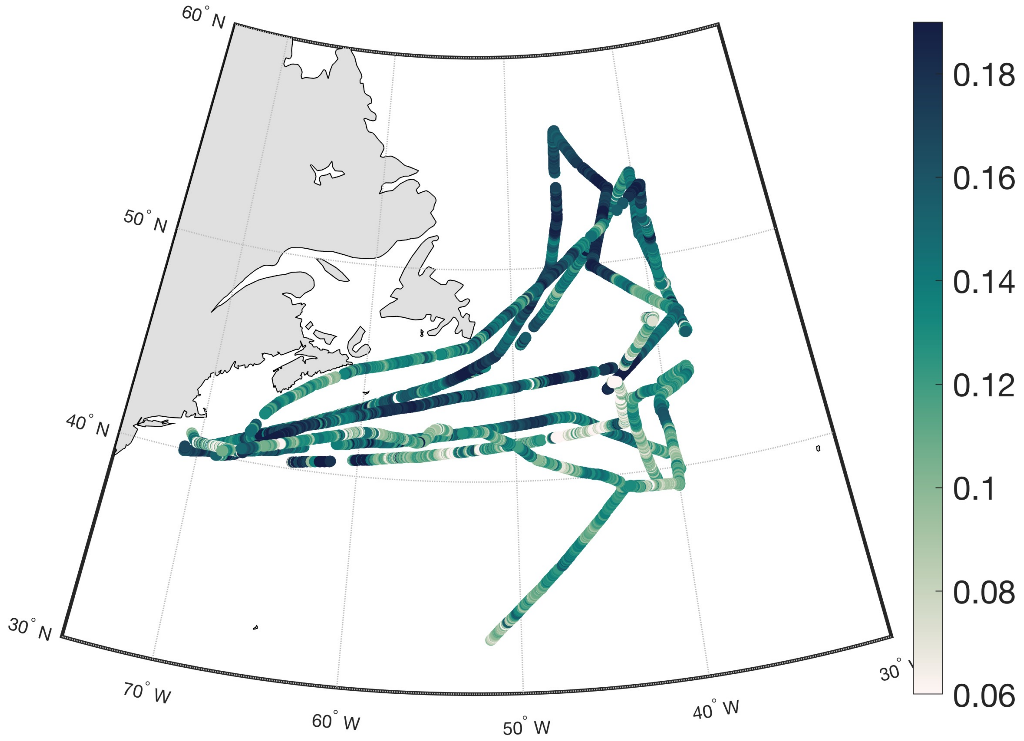
Relative pigment values vary spatially



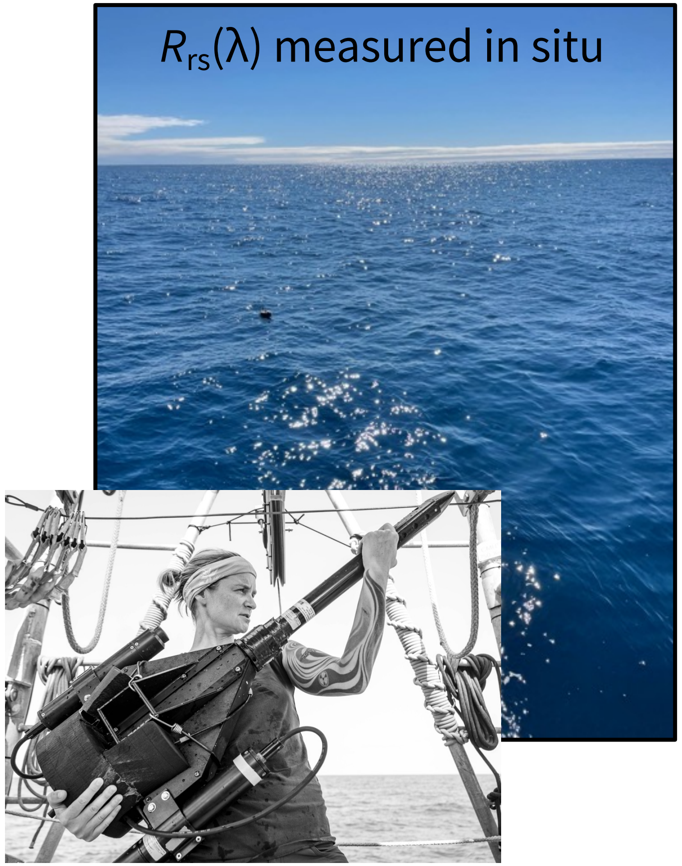
Chlorophyll b : Chlorophyll a



Chlorophyll c : Chlorophyll a



Incorporating Gaussian functions into $R_{rs}(\lambda)$ inversion



$$r_{rs}(\lambda) = \frac{R_{rs}(\lambda)}{0.52 + 1.7R_{rs}(\lambda)}$$

Lee et al. 2002

$$u(\lambda) \equiv \frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)},$$

$$r_{rs}(\lambda) = g_1 u(\lambda) + g_2 u(\lambda)^2$$

$u = u_{meas}$
$g1 = 0.0949$ and $g2 = 0.0794$
(Gordon et al. 1988)

$$u_{mod}(\lambda) = \frac{b_{bp}(\lambda) + b_{bw}(\lambda)}{a_\varphi(\lambda) + a_{CDOM}(\lambda) + a_{NAP}(\lambda) + a_w(\lambda) + b_{bp}(\lambda) + b_{bw}(\lambda)},$$

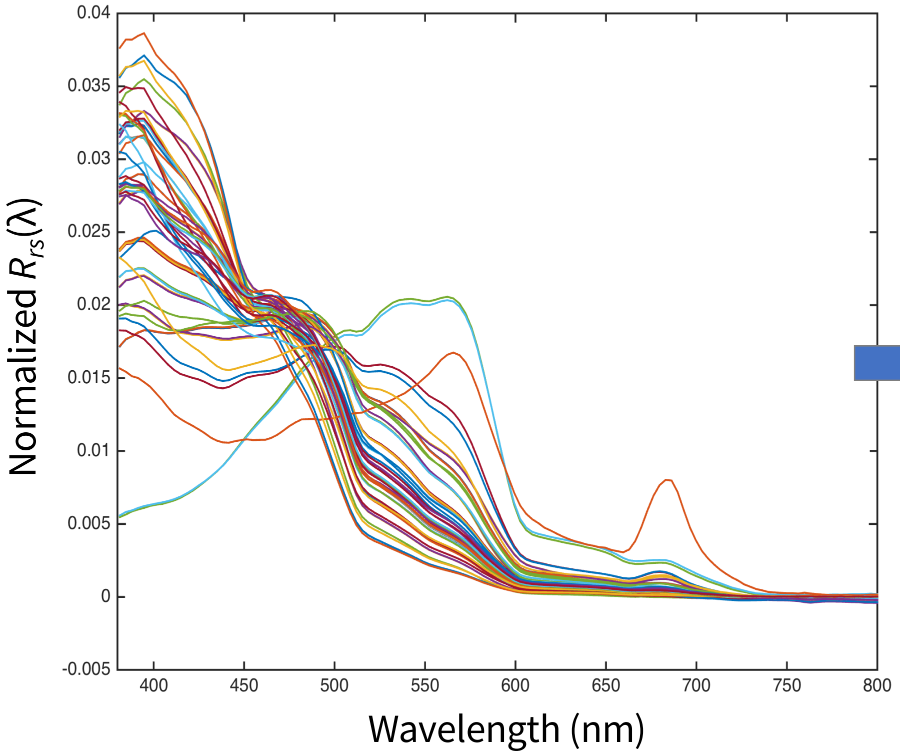
$$a_\varphi(\lambda) = \sum_{i=1}^{8} a_{gaus}(peak_i, \lambda) e^{\left(-0.5\left(\frac{\lambda - peak_i}{\sigma_i}\right)\right)^2},$$

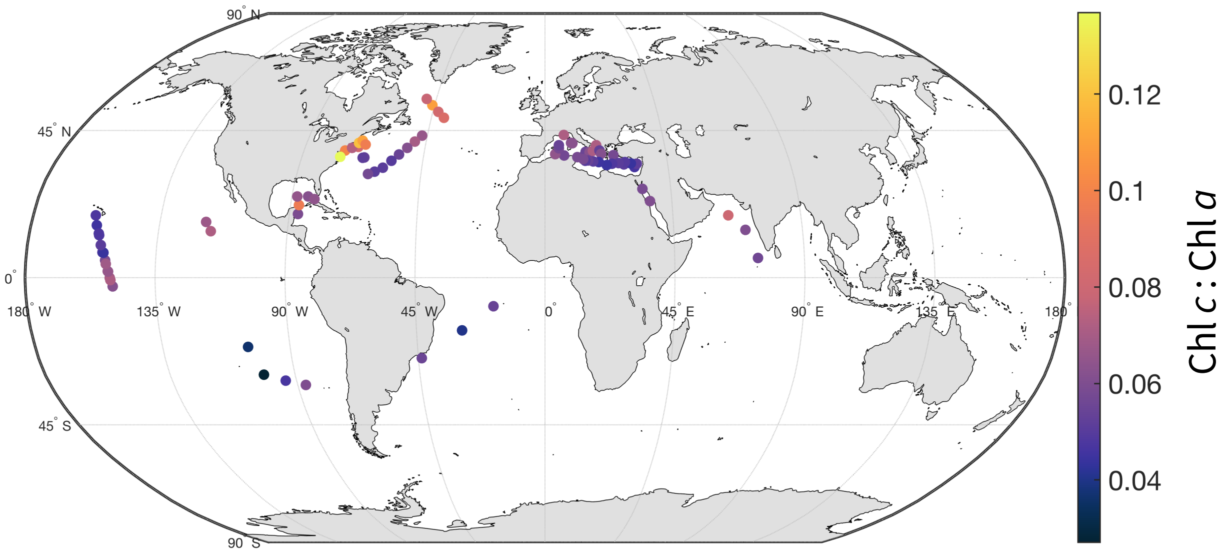
$$\chi^2 = \sum_{i=1}^{60} \left(\frac{u_{meas}(\lambda_i) - u_{mod}(\lambda_i)}{u_{std}(\lambda_i)}\right)^2,$$

60 wavelengths
between 400-600 nm

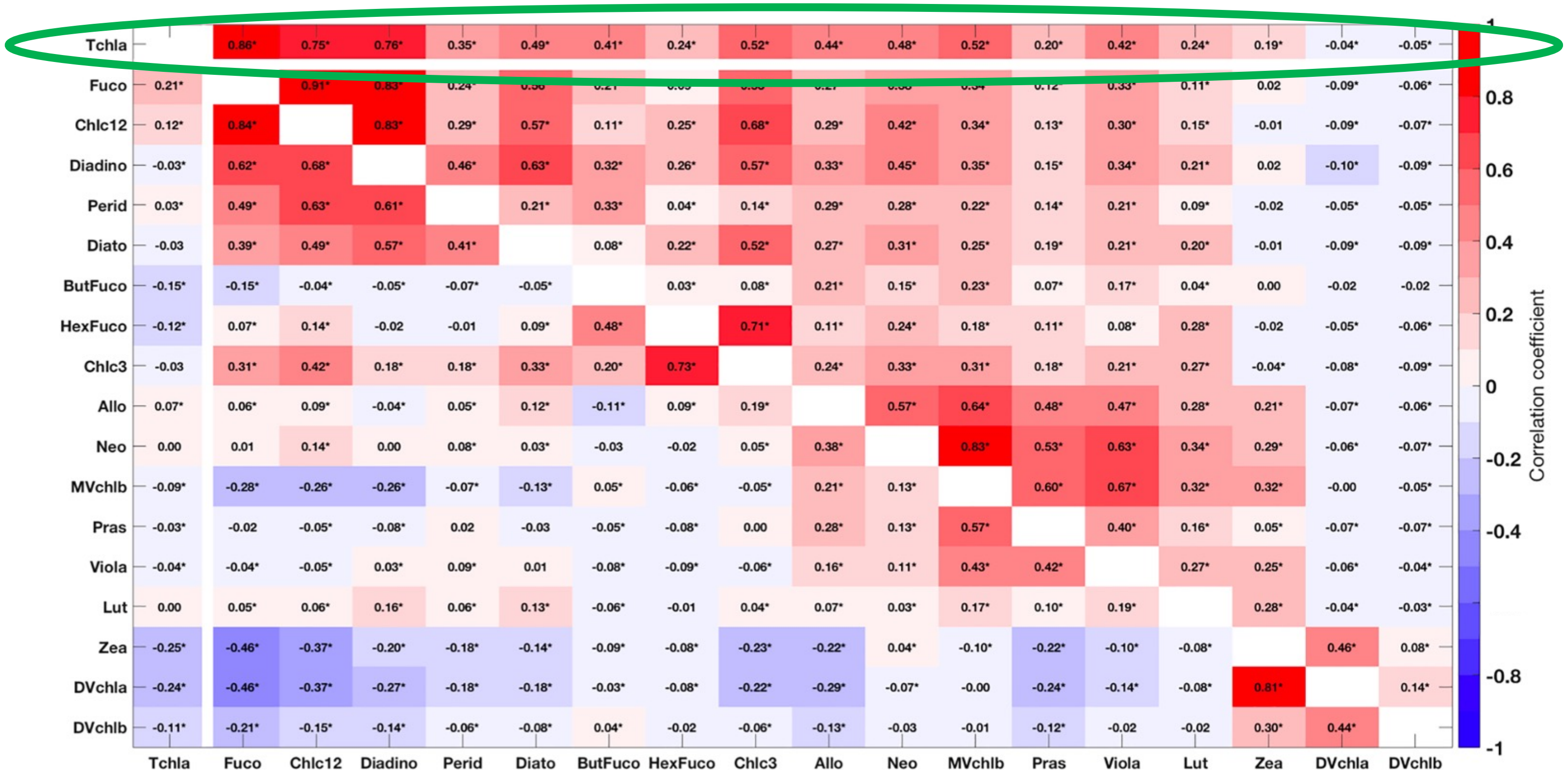
Chase et al. 2017

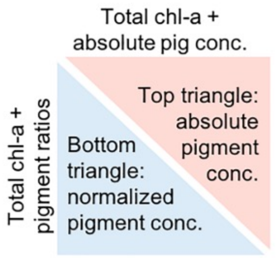
Pigments estimated from $R_{rs}(\lambda)$ spectra measured *in situ*



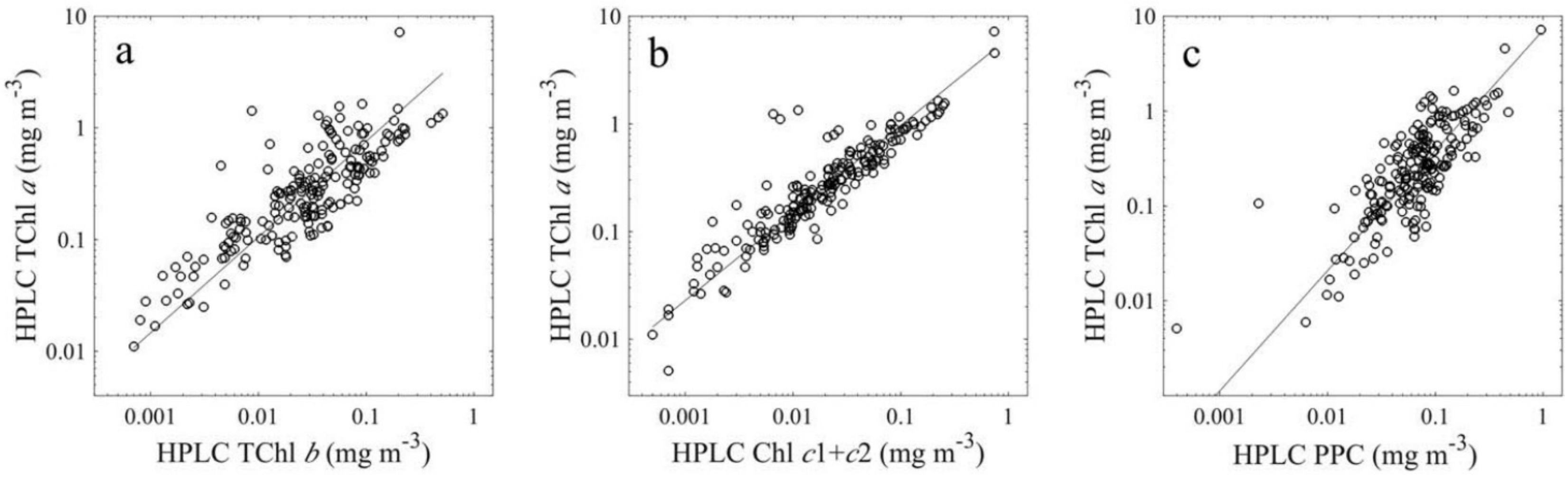


But most pigments are correlated with Chl *a*…





Kramer et al., 2019



Chase et al., 2017

How can we move beyond what is extractable from correlations with Chl *a*?

Considerations of error, & going beyond Chl *a*

From Cael et al. (2020):

- Error is the difference between having four to five DoF rather than >60, and the difference between being able to meaningfully invert for four spectra versus 44

- Some errors such as random electronic noise can be reduced by averaging many measurements in time or space. Others, such a bias in calibration, cannot.

- While all of the optical variation in the water cannot be said to fall along a single axis, it does appear that much of the variation in the surface covaries with [Chl]. Thus, the interest in going “beyond chlorophyll” can be considered an interest in deviations from this axis.

- Polarization will help better separate oceanic and atmospheric contributions to the total signal, and UV will help better separate CDOM, NAP, and phytoplankton contributions to the oceanic signal. These deviations are by definition second order—though we note emphatically that this does not make them unimportant or uninteresting!

- Take home: Judicious use of available DoF; use basis vectors that are specific to your needs in the case of a regional or tuned algorithm

Lecture outline & key topics

Current capabilities of hyperspectral optics & remote sensing

Approaches to extracting information from hyperspectral measurements

Applications to the coastal & complex aquatic ecosystem community

Satellite Ocean Color Based Harmful Algal Bloom Indicators for Aquaculture Decision Support in the Southern Benguela

Marié E. Smith[1] and Stewart Bernard[1,2]*

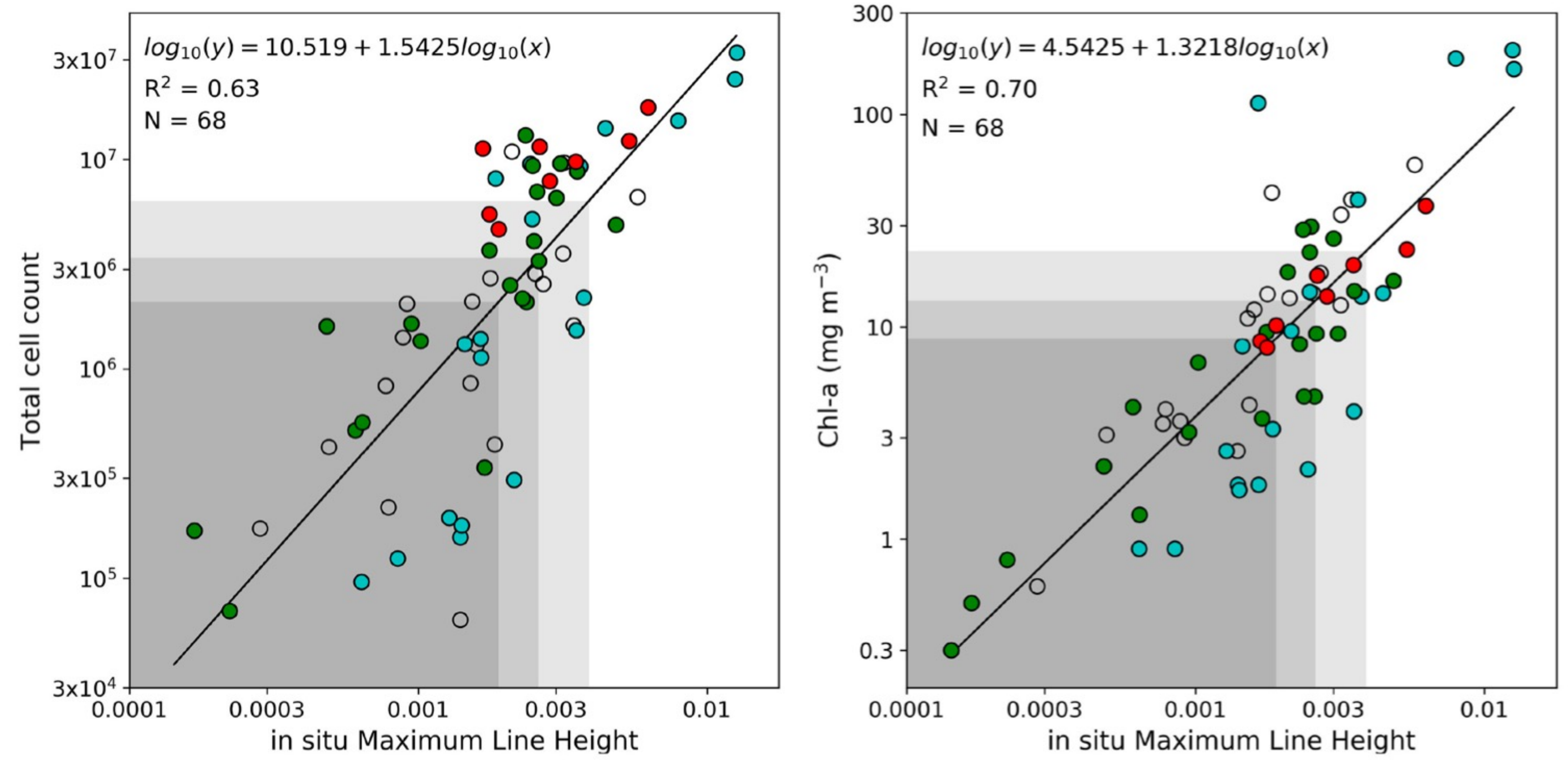


FIGURE 4 | Linear regression analysis between maximum line height and total cell counts **(left)** and between maximum line height and [Chl-a] **(right)**; all data were log-transformed before analysis. The black line represents the regression line with the corresponding equation, coefficient of determination (R^2) and the sample size (*N*). Samples with more than 50% *Pseudo-nitzschia*, diatoms, or dinoflagellates are shown in red, green, and blue, respectively. The shaded areas represent cell counts and [Chl-a] associated with MLH below 0.0019, 0.0027, and 0.0038, respectively.

Smith and Bernard, 2020

remote sensing

MDPI

Article

Spectral and Radiometric Measurement Requirements for Inland, Coastal and Reef Waters

Peter Gege [1,*] and Arnold G. Dekker [2]

Remote Sensing of Environment 240 (2020) 111619

Remote sensing of shallow waters – A 50 year retrospective and future directions

Tiit Kutser[a,*], John Hedley[b], Claudia Giardino[c], Chris Roelfsema[d], Vittorio E. Brando[e]

How do/could you use hyperspectral measurements in your research?

Mentimeter

To study the spectral signature of different optically active substance in estuarine and its coastal region of different water bodies in Indian region.

For an improved optical classification of transitional waters, by providing more information about the water types.

To resample hyperspectral reflectance to satellite wavelength settings (SRF) to do the match-up;

Derive phytoplankton taxa from a drone- improve HAB monitoring/ inform aquaculture.

Above water radiometer (trios) for Atmospheric correction and distinguishing phyto groups!

Resolving phytoplankton pigment signatures

I would use hyperspectral measurements to determine different phytoplankton functional types - in order to link phytoplankton phenology to phytoplankton type

To identify narrow spectral features;

Try and get rid of the Chl-a absorption interference in phycocyanin absorption spectrum

9

Take-home messages:

The question is not as simple as *"how much information can we extract from hyperspectral measurements?"*, **but rather,**

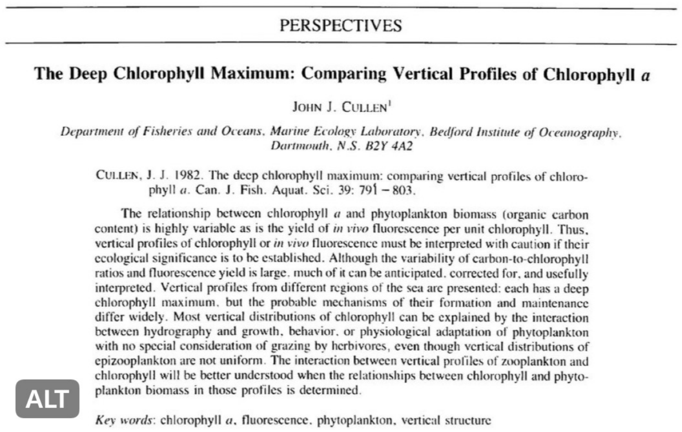
"which approaches and methods that take advantage of the added information in hyperspectral measurements are relevant to my research question(s)?"

With limited degrees of freedom in hyperspectral measurements alone, consider the incorporation of other types of optical and/or environmental data during algorithm development and application, as well as spatial and temporal resolution requirements.

Insights from John Cullen, Professor Emeritus, Dalhousie University, Canada

John Cullen
@JohnCullenOcean

Forty years ago, my first sole-author paper went to press (as in printing). I dredged up some old drafts and the original reviews to illustrate similarities and differences between modern and ancient publications. Some things have changed and some are the same…



PERSPECTIVES

The Deep Chlorophyll Maximum: Comparing Vertical Profiles of Chlorophyll *a*

JOHN J. CULLEN[1]

Department of Fisheries and Oceans, Marine Ecology Laboratory, Bedford Institute of Oceanography, Dartmouth, N.S. B2Y 4A2

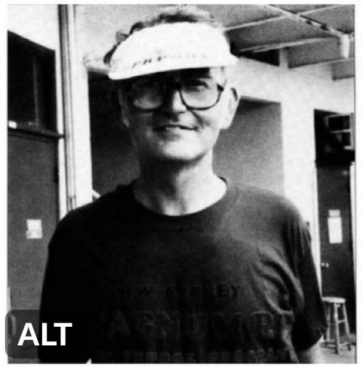
CULLEN, J. J. 1982. The deep chlorophyll maximum: comparing vertical profiles of chlorophyll *a*. Can. J. Fish. Aquat. Sci. 39: 791 – 803.

The relationship between chlorophyll *a* and phytoplankton biomass (organic carbon content) is highly variable as is the yield of *in vivo* fluorescence per unit chlorophyll. Thus, vertical profiles of chlorophyll or *in vivo* fluorescence must be interpreted with caution if their ecological significance is to be established. Although the variability of carbon-to-chlorophyll ratios and fluorescence yield is large, much of it can be anticipated, corrected for, and usefully interpreted. Vertical profiles from different regions of the sea are presented: each has a deep chlorophyll maximum, but the probable mechanisms of their formation and maintenance differ widely. Most vertical distributions of chlorophyll can be explained by the interaction between hydrography and growth, behavior, or physiological adaptation of phytoplankton with no special consideration of grazing by herbivores, even though vertical distributions of epizooplankton are not uniform. The interaction between vertical profiles of zooplankton and chlorophyll will be better understood when the relationships between chlorophyll and phytoplankton biomass in those profiles is determined.

Key words: chlorophyll *a*, fluorescence, phytoplankton, vertical structure

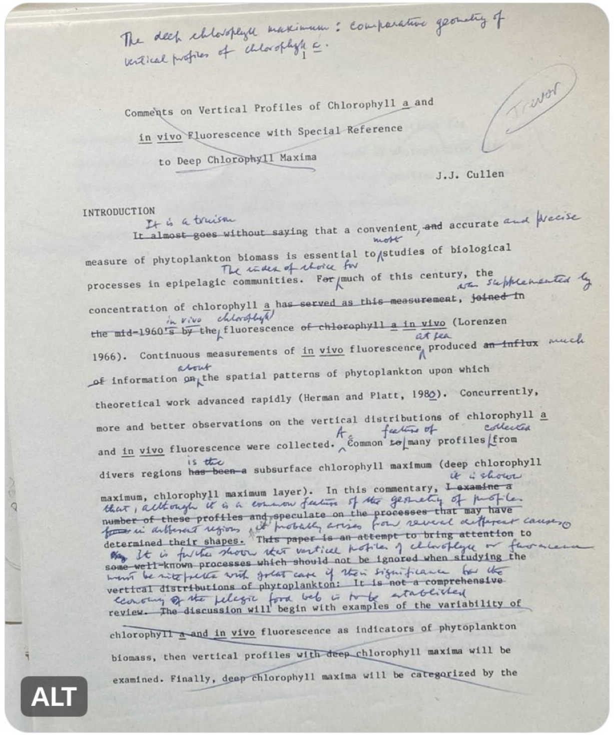
John Cullen @JohnCullenOc… · 5/24/22
Replying to @JohnCullenOcean

The paper addressed the topic I studied under the hugely influential supervision of Richard W. Eppley at the Food Chain Research Group (Scripps). It was written during my post-doc with Trevor Platt at the Marine Ecology Laboratory. Very fortunate to work with world leaders.



John Cullen @JohnCullenOc… · 5/24/22
Trevor Platt, Alan Longhurst and grad student Marlon Lewis commented on the draft — Imagine that!

I considered all comments and made numerous changes. Like many students and post-docs, I eventually forgot that some of the better lines came from my supervisor's edits.



The deep chlorophyll maximum: comparative geometry of vertical profiles of chlorophyll a.

~~Comments on Vertical Profiles of Chlorophyll a and in vivo Fluorescence with Special Reference to Deep Chlorophyll Maxima~~

Trevor

J.J. Cullen

INTRODUCTION

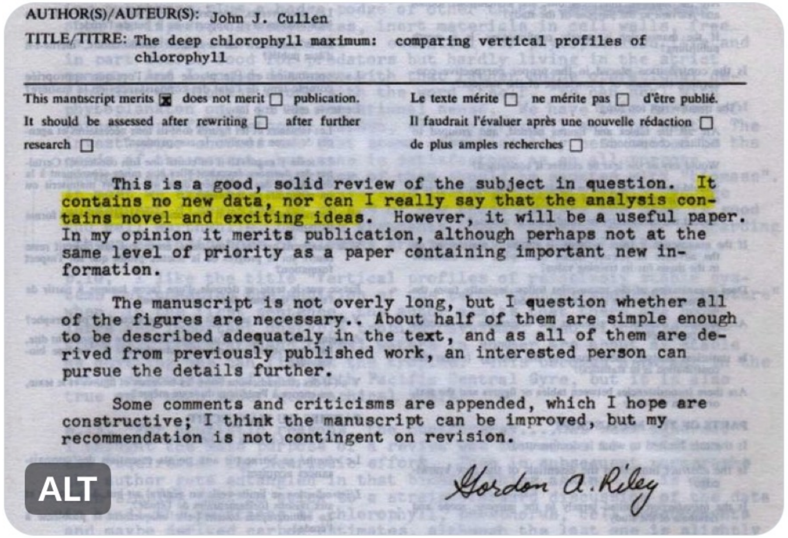
It is a truism ~~It almost goes without saying~~ that a convenient, ~~and~~ accurate and precise measure of phytoplankton biomass is essential to most studies of biological processes in epipelagic communities. The index of choice for ~~For~~ much of this century, the concentration of chlorophyll a has ~~served as this measurement~~, was supplemented by ~~joined in the mid-1960's by~~ the in vivo chlorophyll fluorescence ~~of chlorophyll a in vivo~~ (Lorenzen 1966). Continuous measurements of in vivo fluorescence at sea produced ~~an influx~~ much ~~of~~ information ~~on~~ about the spatial patterns of phytoplankton upon which theoretical work advanced rapidly (Herman and Platt, 1980). Concurrently, more and better observations on the vertical distributions of chlorophyll a and in vivo fluorescence were collected. A common feature of ~~to~~ many profiles collected from divers regions ~~has been a~~ is the subsurface chlorophyll maximum (deep chlorophyll maximum, chlorophyll maximum layer). In this commentary, it is shown ~~I examine a~~ that, although it is a common feature of the geometry of profiles ~~number of these profiles and speculate on the processes that may have~~ ~~found~~ in different regions, it probably arises from several different causes. ~~determined their shapes. This paper is an attempt to bring attention to~~ It is further shown that vertical profiles of chlorophyll or fluorescence ~~some well-known processes which should not be ignored when studying the~~ must be interpreted with great care if their significance for the ~~vertical distributions of phytoplankton: It is not a comprehensive~~ economy of the pelagic food web is to be established ~~review. The discussion will begin with examples of the variability of~~ ~~chlorophyll a and in vivo fluorescence as indicators of phytoplankton biomass, then vertical profiles with deep chlorophyll maxima will be examined. Finally, deep chlorophyll maxima will be categorized by the~~

John Cullen @JohnCullenOc... · 5/24/22 ···

Peer review:

THE Gordon Riley (retired) provided comments promptly. He generously allowed me to follow up with a phone call that was a treat (I never met him).

The paper did not offer much to an expert like him, but he was supportive of an early-career researcher.



AUTHOR(S)/AUTEUR(S): John J. Cullen
TITLE/TITRE: The deep chlorophyll maximum: comparing vertical profiles of chlorophyll

This manuscript merits ☒ does not merit ☐ publication. Le texte mérite ☐ ne mérite pas ☐ d'être publié.
It should be assessed after rewriting ☐ after further research ☐ Il faudrait l'évaluer après une nouvelle rédaction ☐ de plus amples recherches ☐

This is a good, solid review of the subject in question. It contains no new data, nor can I really say that the analysis contains novel and exciting ideas. However, it will be a useful paper. In my opinion it merits publication, although perhaps not at the same level of priority as a paper containing important new information.

The manuscript is not overly long, but I question whether all of the figures are necessary. About half of them are simple enough to be described adequately in the text, and as all of them are derived from previously published work, an interested person can pursue the details further.

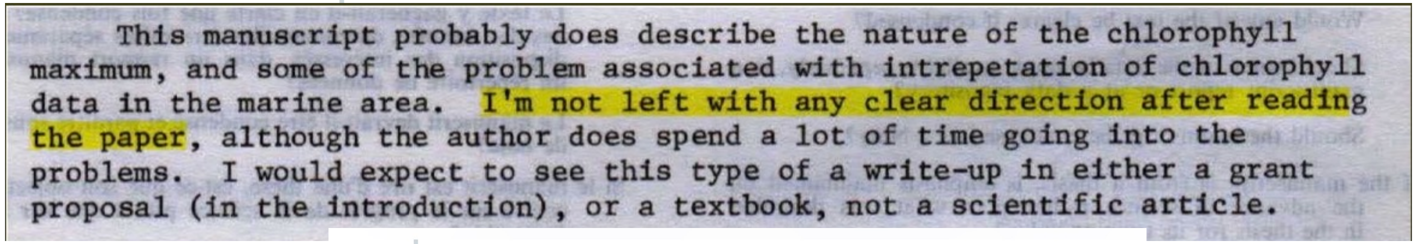
Some comments and criticisms are appended, which I hope are constructive; I think the manuscript can be improved, but my recommendation is not contingent on revision.

Gordon A. Riley

ALT

John Cullen @JohnCullenOc... · 5/24/22 ···

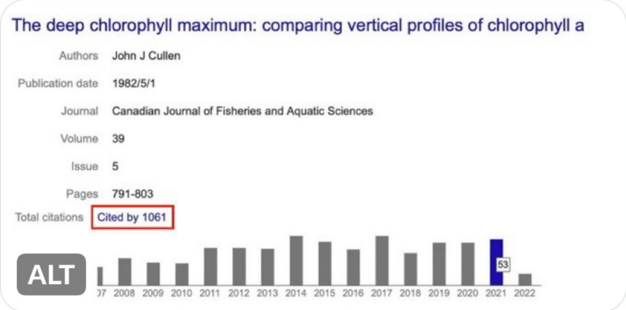
2nd referee's comments in full, after a 4-month wait. This kind of review, familiar to many, should be called what it is: lazy, arrogant and irresponsible. How many papers have been spiked by reviews like this? Fortunately, the editor dismissed it as "not worth waiting for."



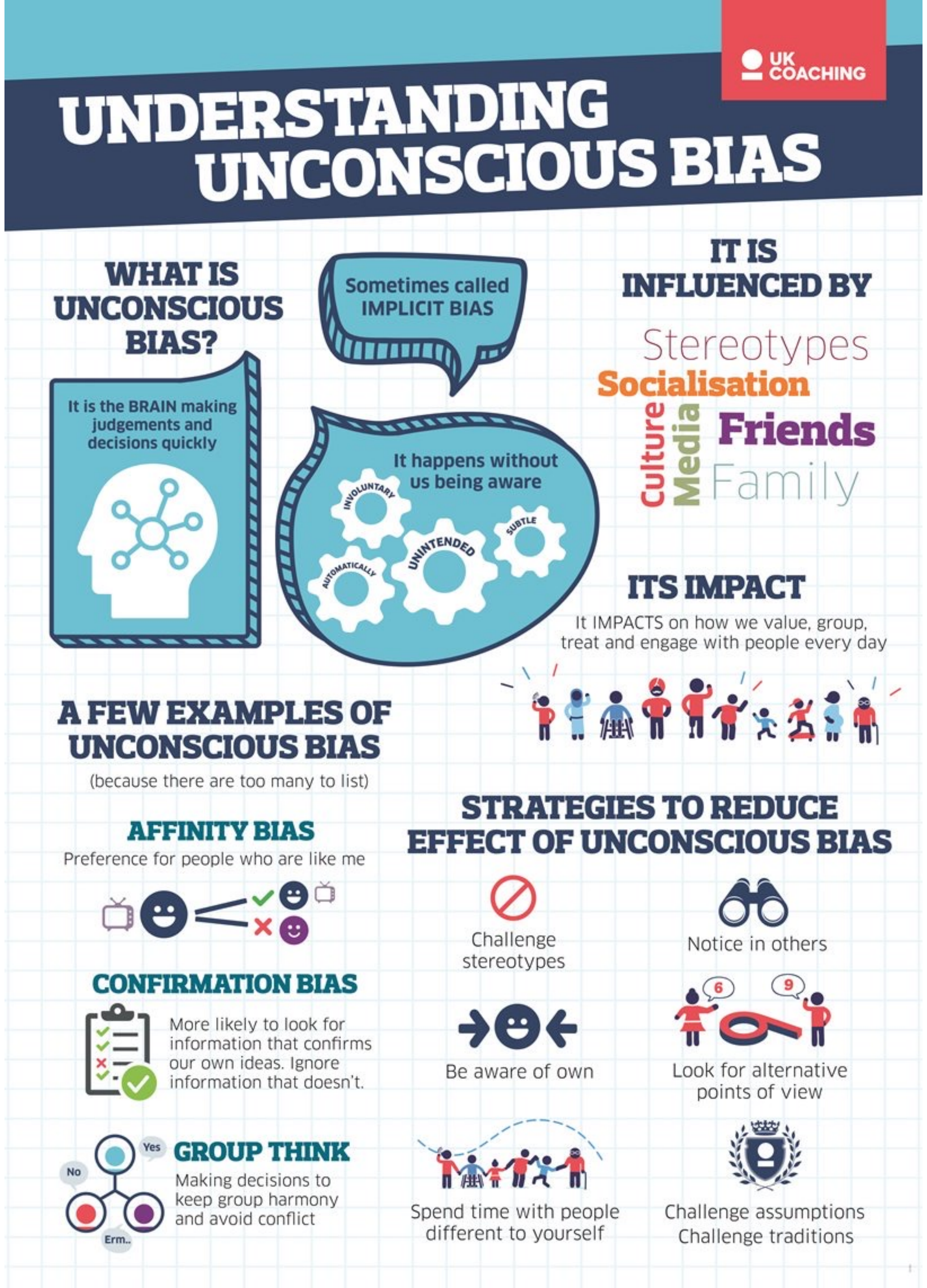
This manuscript probably does describe the nature of the chlorophyll maximum, and some of the problem associated with intrepetation of chlorophyll data in the marine area. I'm not left with any clear direction after reading the paper, although the author does spend a lot of time going into the problems. I would expect to see this type of a write-up in either a grant proposal (in the introduction), or a textbook, not a scientific article.

John Cullen @JohnCullenOc... · 5/24/22 ···

40 years on, it is the top-cited article from the journal that year. Editor David Cook made the right call in dismissing "Reviewer 2" and relying on Gordon Riley, who was generous and constructive, if not enthusiastic. My research supervision was great. As always, people matter.




Don't think outside the box.
Think like there is no box.



https://www.ukcoaching.org/resources/topics/diagram-infographic/understanding-unconscious-bias


Thank you!

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Box 1. Satellite Sensors

AVIRIS: Airborne Visible/Infrared Imaging Spectrometer developed by NASA's Jet Propulsion Laboratory

CHIME: Copernicus Hyperspectral Imaging Mission for the Environment

CHRIS: Compact High Resolution Imaging Spectrometer aboard the European Space Agency's PROBA-1 satellite

DESIS: DLR (German Aerospace Center) Earth Sensing Imaging Spectrometer, a hyperspectral sensor developed and operated collaboratively by the DLR and Teledyne Brown Engineering

EnMAP: Environmental Mapping and Analysis Program, a German hyperspectral satellite mission

HICO: Hyperspectral Imager for the Coastal Ocean, an imaging spectrometer that was housed on the International Space Station

MODIS: Moderate Resolution Imaging Spectroradiometer, a key instrument aboard NASA's Terra and Aqua satellites

PACE: NASA's Plankton, Aerosol, Cloud, ocean Ecosystem mission

PRISM: Picosatellite for Remote-sensing and Innovative Space Missions, a technology pathfinder mission of the Intelligent Space Systems Laboratory at the University of Tokyo, Japan

PRISMA: Hyperspectral Precursor and Application Mission, a medium-resolution hyperspectral imaging mission of the Italian Space Agency

SCIAMACHY: An ESA imaging spectrometer whose primary mission was to perform global measurements of trace gases in the troposphere and stratosphere

SBG: NASA's Surface Biology and Geology mission (formerly HyspIRI)

TROPOMI: TROPOspheric Monitoring Instrument onboard the ESA Copernicus Sentinel-5 Precursor satellite

Dierssen et al., 2020

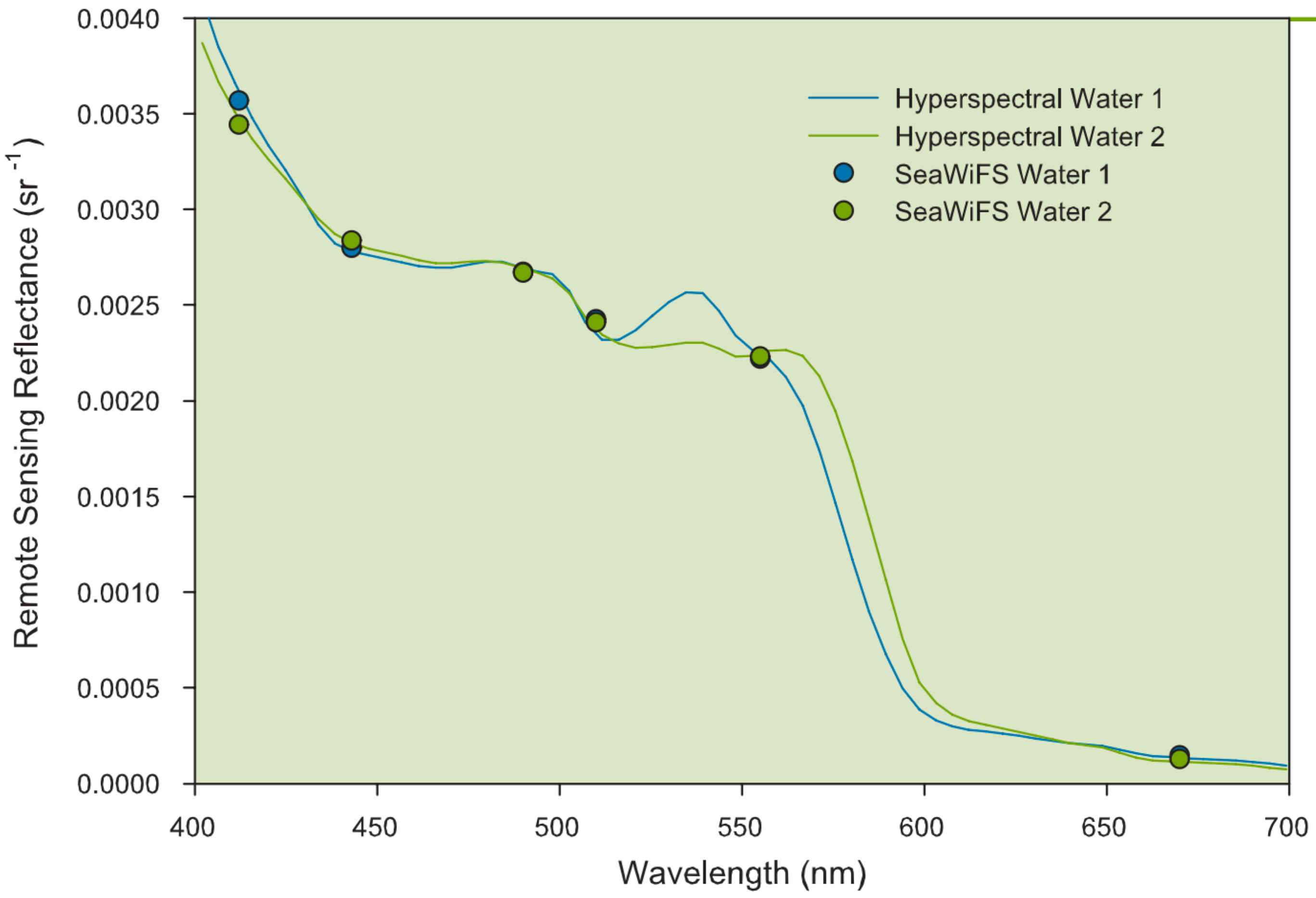

Figure 2. Bottom effects in shallow coastal waters may lead to inaccurate remote sensing retrievals of bottom depth if limited spectral bands are utilized for analysis. This figure shows modeled hyperspectral (solid lines) and multispectral (SeaWiFS wavebands; circles) spectra for two water types, generated by the Hydrolight radiative transfer model (Mobley, 1994). Water 1 (blue) is 6.5 m deep and has low chlorophyll-a and CDOM concentrations with a bottom type of a mixture of soft coral and *Sargassum*, while Water 2 (green) is 13 m deep, "pure water" with a flat green sponge bottom type. By inspection of the hyperspectral spectra, the difference between the two curves is obvious in the 500-600 nm range. However, spectra for the two water types produced using only the SeaWiFS wavebands appear almost identical. (SeaWiFS spectra in this figure were derived by applying the SeaWiFS spectral response function to the hyperspectral signatures).

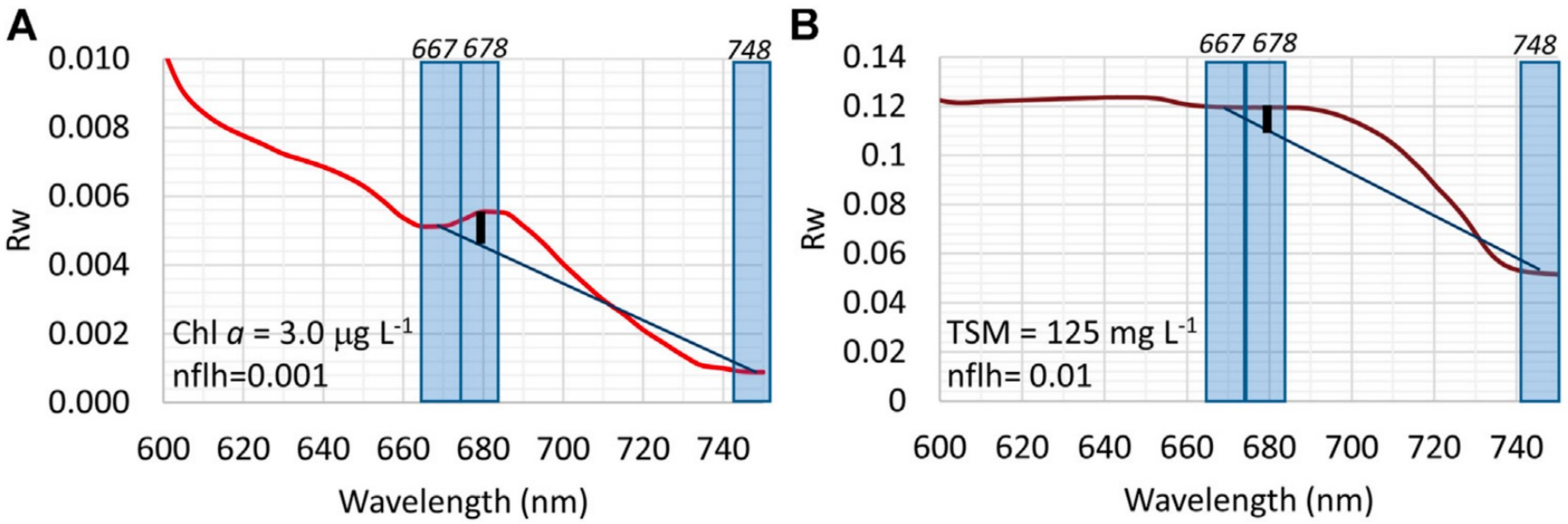

FIGURE 3 | Narrowband features like chlorophyll fluorescence can be inaccurately estimated when using multi-spectral bands that are distant from the feature, such as the blue bands used in the normalized fluorescence line height (nflh). Examples of **(A)** water-leaving Reflectance (Rw) spectrum with a typical chlorophyll fluorescence feature and **(B)** a spectrum representative of high sediment water with no observable chlorophyll fluorescence leads to an erroneously high nflh.